A Unified Framework for *Value* and *Momentum*

Jacob Boudoukh, Tobias Moskowitz, Matthew Richardson, and Lei Xie*

Abstract:
A simple unifying present value framework provides an understanding for *value* and *momentum* effects in asset prices. Through the present value formula, valuation ratios adjusted for expected future earnings growth provide estimates of expected returns. We argue and show that *momentum* is a reasonable proxy for growth. Momentum forecasts future earnings growth, significantly improves *value*'s forecast for expected returns, and is drowned out when accounting for future realized growth. Extending the analysis to more general earnings growth models, we construct theoretically-motivated single factor models based on growth-adjusted *value* that price the cross-section of assets well relative to popular multifactor models.

* Jacob Boudoukh (Arison School of Business, IDC), Tobias Moskowitz (Yale University, AQR Capital Management, and NBER), Matthew Richardson (Stern School of Business, NYU, NBER and consultant to AQR Capital Management) and Lei Xie (Point72). We thank Cliff Asness, Xavier Gabaix, Esben Hedegaard, Ronen Israel, John Liew, Lasse Pedersen, Scott Richardson, Laszlo Szocs, Jeremy Stein, and Robert Whitelaw, as well as seminar participants at NYU, the AQR Colloquium, Oxford University and Reisman University, for helpful comments.

I. Introduction

Two important characteristics/factors describing the cross-section of expected stock returns are a firm's valuation ratio, such as price-to book, earnings, or dividends – often termed the *value* effect, and a firm's medium-term history of past returns – the *momentum* effect.[1] These two characteristics explain expected stock returns not just in U.S. equity markets, but globally across many markets and asset classes, and through many time periods.[2] The ubiquitous presence of *value* and *momentum* presents a challenge to theory, either behavioral or risk-based, to provide a unified framework for their co-existence. Most explanations of the *value* and *momentum* effects are provided in isolation.[3] This paper provides a simple unifying explanation for the co-existence of *value* and *momentum* effects in pricing assets, as well as their interaction, based simply on the present value model (Gordon (1959)). The explanation does not rely on a theory of under- or over-reaction, which often underlies theories for these effects.

The present value model implies that valuation ratios are high (low) either because expected future cash flow growth is high (low) or because expected returns are low (high). Backing out reliable expected returns from this model requires that valuation ratios be adjusted for expected future cash flow growth. The problem is that expected future cash flow growth is unobservable. Our insight recognizes that *momentum* is a reasonable, though noisy, proxy for future growth, thus linking expected returns jointly to *value* and *momentum*. From this simple point of view, and to the extent the present value model is a reasonable description of reality, *value* and *momentum* effects should co-exist for stocks in all countries and over time, consistent with the prevailing evidence. These two characteristics are built-in features of the valuation formula. Their predictive ability for expected returns can simply be interpreted through the present value relation. This framework is consistent with both rational and behavioral forces that may drive prices, but, importantly, provides a link between *value* and *momentum* and how they relate to expected returns simultaneously.

This unified framework highlights several properties. First, *momentum* should forecast future earnings growth. Second, because *value* and *momentum* are structurally linked via the present value model,

---

[1] An extensive literature documents value and *momentum* effects. For initial studies on *value*, see Statman (1980), Basu (1983), Rosenberg, Reid and Lanstein (1985), and Fama and French (1992). Subsequent studies include Fama and French (1996), Daniel and Titman (1997), Brennan, Chordia and Subrahmanyam (1998), Zhang (2005), Boudoukh, Michaely, Richardson and Roberts (2007) and Asness, Moskowitz, and Pedersen (2013), among others. For *momentum*, see Jegadeesh and Titman (1993) and Asness (1994), with later studies by Carhart (1997), Moskowitz and Grinblatt (1999), Hong and Stein (2000), Jegadeesh and Titman (2001), Chordia and Shivakumar (2006), and Asness, Moskowitz, and Pedersen (2013), among others.

[2] In terms of international evidence, see, for example, Fama and French (1998) for an investigation of value stocks; Rouwenhorst (1998), Chan, Hameed, and Tong (2000), and Griffin, Ji and Martin (2003) for studies of *momentum*; and Hou, Karolyi and Kho (2011), Fama and French (2012) and Asness, Moskowitz and Pedersen (2013) for an analysis of both *value* and *momentum*. Asness, Moskowitz, and Pedersen (2013) examine all major asset classes.

[3] For papers focusing on the interaction between *value* and *momentum*, see, for example, Asness (1997), Asness, Moskowitz, and Pedersen (2013), Liu and Zhang (2014), Fisher, Shah, and Titman (2016), and Li (2017).

univariate regressions of returns on *value* or *momentum* will not fully recover the relationship. *Value* and *momentum* should work much better together. Third, if *momentum*'s primary channel is via its relationship to future growth, then realized future growth should crowd out and subsume *momentum* in a present value framework. We test and find evidence in favor of all three predictions, supporting this unified view for *value* and *momentum* effects in asset pricing.

While the primary focus of the empirical analysis is on the cross-section of individual U.S. stocks, we also extend the analysis to stocks across 23 developed equity markets, including Japan, where the existing literature suggests *momentum* does not work well (Chui, Titman, and Wei (2010)). We also seek to understand the return patterns at the industry level, where the literature finds *momentum* is strong (Moskowitz and Grinblatt (1999)) and *value* is weak (Asness, Porter, and Stevens (2000), Cohen and Polk (1998)). We find that *momentum* strengthens the link between *value* and expected returns in all markets and for industry portfolios, consistent with the present value interpretation of *momentum* as a proxy for expected growth. These results showcase that *value* and *momentum* should be thought of simultaneously, as a system, with the present value formula providing the link. When doing so, the combination of *value* and *momentum* works similarly across markets and segments of markets, even though *value* and *momentum* on their own may work quite differently across markets or sample periods.

The present value theory is not about *momentum* and *value* per se, but more generally valuation and expected future cash flow growth. We extend our analysis to include other models of expected earnings growth, providing a role for not just price *momentum*, but also analysts' earnings forecasts. The results are consistent for this alternative measure of earnings growth. Consistent with theory, the more precise measures of earnings growth produce stronger return predictability.

Applying these insights, we construct a new single pricing factor, *growth-adjusted value*, and compare it to popular multifactor models from the literature, including the Fama-French-Carhart 4-factor model. We consider three different growth-adjusted *value* factors, one using *momentum* as a proxy for growth, another using a combination of *momentum* and analysts' earnings forecasts as a proxy for growth, and finally using realized earnings growth to adjust *value*, which is an infeasible factor to construct in real time, but provides an upper bound on the efficacy of the simple growth-adjusted value factor. We find supportive evidence in favor of our single factor relative to the aforementioned multi-factor models. We also provide evidence that our growth-adjusted *value* factor can help with some, though not all, of the better-known return anomalies.

Interpreting our results optimistically, we find it impressive that a single factor derived from the simple present value model prices assets well compared to popular multi factor models. On the other hand, the model we use is simple and limited, leaving scope for improvement. Differing results across various versions of our single growth-adjusted *value* factor present a challenge and opportunity for future research, where the present value model provides a guiding framework to derive more precise expected return forecasts that may be promising.

Of course, the point that the present value model can pin down expected returns does not necessarily help explain what economic risks or behavior drive these expected returns. For example, nothing in our framework precludes a behavioral explanation for either *momentum* or *value*. However, the insights and supporting evidence in this paper show that behavioral explanations, such as over- and underreaction commonly used to explain both phenomena (e.g., Daniel, Hirshsleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999)), are not *necessary* ingredients. The present value model simply implies a significant joint role for both *value* and *momentum* in describing conditional expected returns, and this framework may provide a good starting point to investigate underlying economic theories for the coexistence of *value* and *momentum* in asset pricing.

The rest of the paper is organized as follows. Section II provides a unified theoretical framework for *value* and *momentum* effects in asset prices. Section III presents empirical evidence supporting this framework. Section IV examines asset pricing implications and develops a one-factor model of *value* and *momentum* consistent with theory that prices the cross-section of assets. Section V concludes.

II. Unified Framework for *Value* and *Momentum*: Theory

We present a unified present value framework to interpret *value* and *momentum* effects.

A. The Present Value Model

The Gordon (1959) growth model (GGM) relates the current value of a firm to the present value of its cash flows, discounted at a constant cost of capital. Essentially, all versions of the model imply a firm's price multiple

$$\frac{P_i}{CF_i} = \lambda_i \frac{1}{E[R_i] - E\left[g_{CF_i}\right]} \qquad (1)$$

where P_i is the stock price of firm i, CF_i is a measure of the firm's cash flows (such as dividends, earnings or book value), $E\left[g_{CF_i}\right]$ is the expected growth rate of the firm's cash flows, $E[R_i]$ is the expected return on the firm's equity (i.e., cost of capital), and λ_i is a parameter specific to the particular version of the

GGM.[4] The model implies that a stock's price multiple can be high because expected growth rates are high or because expected returns are low.

The GGM model in equation (1) can be rewritten in terms of expected returns, namely

$$\mathrm{E}[R_i] = \lambda_i Val_i + E\left[g_{CF_i}\right] \qquad (2)$$

where $Val_i \equiv \left(\frac{P_i}{CF_i}\right)^{-1}$, the *value* measure for stock *i*. To gain some intuition, compare two stocks, *j* and *k*. Assume the parameter value λ_i is the same for stock *j* and *k*. Holding expected growth, $E\left[g_{CF_i}\right]$, constant, stock *k* has a higher expected return than stock *j* if it has a higher *value* measure (i.e., lower valuation ratio) due to higher risk for the same expected growth rate. The problem with this interpretation, however, is that Val_i likely depends on $E\left[g_{CF_i}\right]$. Stock *k* may have a higher valuation ratio than stock *j* not because of risk but rather because firm *k* has higher expected growth. Equation (2), therefore, implies that stock *k* and *j* may have similar expected returns because stock *k*'s lower *value* measure is offset by its higher expected growth. This point illustrates the key implication from equation (2), namely that cross-sectional variation in expected returns can only be uncovered by measuring *jointly* the current valuation ratios *and* the expected future cash flow growth rates. As long as the expected cash flow growth rate is not constant across firms, empirically estimating expected returns from just the *value* measure suffers from an omitted variable bias, whose implications we explore below.

B. *Omitted Variable Bias and Value's Relation to Expected Returns*

Note that the GGM equation (2) assumes constant expected returns. An estimate of expected returns are average future realized returns. In order to empirically operationalize equation (2), at each time *t*, we therefore run a cross-sectional Fama-MacBeth regression of R_{it+1} on expected future cash flow growth over the life of the stock, $E_t\left[g_{CF_{it\infty}}\right]$, and its *value*, Val_{it}, at time *t*:[5]

$$R_{it+1} = \alpha + \gamma E_t\left[g_{CF_{it\infty}}\right] + \delta Val_{it} + \varepsilon_{it+1}, \forall\, i = 1, \dots, N \qquad (3)$$

[4] For the version of GGM with dividends, $\lambda_i = 1$; with earnings, $\lambda_i = (1 - p_i)$, where $D_i = (1 - p_i)e_i$, and p_i is the plowback ratio and e_t the earnings of the stock; and, with residual income, $\lambda_i = (ROE_i - R_i)$, where $ROE_i = {}^{e_i}/_{B_i}$, where B_i is the book value of firm *i* and R_i the constant cost of capital $E[R_i]$ (e.g. Ohlson (1995)). In practice, researchers choose different measures of earnings, including net income, forward earnings forecasts from analysts, and moving average of past earnings (adjusting for inflation so as to keep earnings in the same units, denoted cyclically adjusted price-to-earnings (CAPE)).

[5] Note that while $E_t\left[g_{CF_{it\infty}}\right]$ measures future expected realized growth, we measure its magnitude in units from time *t* to *t*+1 (e.g., daily, monthly, annualized, etc…) corresponding to the return horizon in equation (3).

The regression coefficients can be written as, $\gamma = \frac{\sigma_R \rho_{R,Eg}}{\sigma_{Eg}\left(1-\rho_{V,Eg}^2\right)} - \frac{\sigma_R \rho_{R,V} \rho_{V,Eg}}{\sigma_{Eg}\left(1-\rho_{V,Eg}^2\right)}$ and $\delta = \frac{\sigma_R \rho_{R,V}}{\sigma_{VAL}\left(1-\rho_{V,Eg}^2\right)} - \frac{\sigma_R \rho_{R,Eg} \rho_{V,Eg}}{\sigma_{VAL}\left(1-\rho_{V,Eg}^2\right)}$, which we will decompose using proxies for expected future cash flow growth below. The regressions are run cross-sectionally at every point in time and the time-series average of the coefficients are calculated in the style of Fama and MacBeth (1973), with time-series standard errors.

As Campbell and Shiller (1988) show, the GGM does not require constant expected returns and growth rates (see also Sadka and Sadka (2009), Binsbergen and Koijen (2010), Koijen and Van Nieuwerburgh (2011), Golez (2014), and Da, Jagannathan and Shen (2014)). Valuation ratios can be derived from predictable changes in discount rates and cash flow growth rates. The dynamic version of the GGM is often written in terms of vector autoregressions of cash flow growth, where expected returns over a given period can be expressed in terms of a limited number of state variables describing $E_t\left[g_{CF_{it\infty}}\right]$.

From an econometric viewpoint, there is estimation error in valuation measures. Consider the dividend-price-ratio. A problem with using dividends as the measure of cash flow is that (i) there is no necessary link between current dividends and stock prices (Miller and Modigliani (1961)), (ii) there are many ways to distribute cash flows to shareholders (Boudoukh, Michaely, Richardson, and Roberts (2007)), and (iii) dividends are commonly thought of as time-smoothed versions of firm cash flows (Chen, Da, and Priestley (2012)). Similarly, the earnings-to-price ratio contains error if current earnings are a noisy measure of future earnings or growth. Replacing current earnings with consensus analysts' forward earnings forecast, or, a moving average of past earnings (adjusting for inflation so as to keep earnings in the same units) are also fraught with measurement error. Researchers often choose book-to-market as a valuation measure as well, to avoid these issues, but book value has its own measurement issues (e.g., see Asness and Frazzini (2013), Gu and Lev (2017), Peters and Taylor (2017) and Eisfeldt, Kim and Papanikolaou (2020)). It is an empirical issue as to how much measurement error exists in these value metrics and how that matters for explaining asset prices.

In contrast to *value*, expected future cash flow growth is neither well-defined nor directly observable, which presents another measurement problem. To illustrate how measurement error affects return predictability, and how the present value relation can help clear it up, assume the following: the econometrician observes $\hat{g}_{CF_{it}}$, which captures the true expected growth rate plus error, $\hat{g}_{CF_{it}} = E_t\left[g_{CF_{it\infty}}\right] + \upsilon_{it+1}$, and assume (for now) that VAL_{it} is measured without error (we will deal with error in the value metric later).

Equation (2) implies that expected returns are fundamentally related to *value* and expected future growth. By running a univariate regression of realized returns on either *value* or expected future growth separately, the cross-sectional regression in (3) will suffer from a combination of omitted variables bias and, in the case of a growth regression, an errors-in-variable bias. Focusing on the coefficient on *value*, δ,

$$\begin{aligned}\text{plim}\left[\delta^*\right] &= \frac{\delta\sigma_{Val}^2 + \gamma \operatorname{cov}\left(Val, Eg\right)}{\sigma_{Val}^2} \\ &= \delta + \gamma \frac{\rho_{Val,Eg}\sigma_{Eg}}{\sigma_{Val}}\end{aligned} \tag{4}$$

Due to omitted variables, the coefficient on *value* in the univariate regression, δ^*, is most likely a downward biased estimate of the true coefficient δ (which is positive according to theory and equation (2)). The adjustment is negative because γ is positive according to the same theory, and $\rho_{V,Eg}$, the correlation between *value* and expected future growth, is most likely negative. This latter condition is due to a stock's higher valuation ratio being partly due to higher expected future growth. In other words, not all the variation in valuation ratios comes from variation in expected returns (e.g., Vuolteenaho (2002), Cohen, Polk, and Vuolteenaho (2003), Callen and Segal (2004) and Chen, Da, and Zhao (2013)). The key point here is that, in the GGM framework, $\delta^* \neq \delta$ because *both* $\gamma > 0$ and $\rho_{V,EG} < 0$. The negative correlation $\rho_{V,EG} < 0$ is not sufficient and the model restriction in equation (2), $\gamma > 0$, is also necessary.

The true estimate of the effect of *value* on future stocks returns can only be uncovered if both *valu*e and expected future growth are included together, as implied by equation (2). What then is the impact of running a multivariate regression and including a noisy proxy of expected future growth? The coefficient in equation (4) will tend to increase relative to the univariate case because both *value* and expected future growth are positively correlated with future expected returns, and are themselves negatively correlated. Measurement error still, however, can have an important effect. Specifically, with measurement error in expected future growth, the coefficient on value from a bivariate regression of future returns on *value* and the growth proxy is:

$$\begin{aligned}\text{plim}\left[\delta^{**}\right] &= \frac{\left(\sigma_{Eg}^2 + \sigma_v^2\right)\operatorname{cov}\left(R, Val\right) - \operatorname{cov}\left(Val, Eg\right)\operatorname{cov}\left(R, Eg\right)}{\left(\sigma_{Eg}^2 + \sigma_v^2\right)\sigma_{Val}^2 - \operatorname{cov}\left(Val, Eg\right)^2} \\ &= \delta + \frac{\rho_{Val,Eg}\sigma_{Eg}}{\sigma_{Val}}\left(\gamma - \text{plim}\left[\gamma^{**}\right]\right)\end{aligned} \tag{5}$$

where $\gamma - \text{plim}\left[\gamma^{**}\right] = \gamma\left(\frac{\sigma_v^2}{\sigma_v^2 + \sigma_{Eg}^2\left(1 - \rho_{Val,Eg}^2\right)}\right)$

The formula resembles the well-known formula for the ordinary least squares coefficient with errors-in-variables, except there is now an adjustment for the contemporaneous correlation between *value* and expected future growth. The coefficient on *value*, δ^{**}, is still biased downward relative to its true value because the coefficient on expected future growth, γ^{**}, is biased downward, and the correlation between *value* and expected future growth is negative. The bias in equation (5) is less than that of the univariate estimator, δ^{*}, in equation (4). In particular,

$$\text{plim}\left[\delta^{**}-\delta^{*}\right]=-\frac{\rho_{Val,Eg}\sigma_{Eg}}{\sigma_{Val}}\gamma\left(\frac{\sigma_{Eg}^{2}\left(1-\rho_{Val,Eg}^{2}\right)}{\sigma_{v}^{2}+\sigma_{Eg}^{2}\left(1-\rho_{Val,Eg}^{2}\right)}\right)>0. \tag{6}$$

If $\sigma_v^2 \approx 0$ in equation (6) (i.e., there is no measurement error), then the difference $plim[\delta^{**} - \delta^{*}]$ equals $-\gamma \frac{\rho_{V,Eg}\sigma_{Eg}}{\sigma_{Val}}$ and is higher the more negatively correlated *value* and realized growth are. If $\sigma_v^2 \approx \infty$ (i.e., very large measurement error), then the difference tends to zero and the estimates are both biased in the same way. Negative correlation is irrelevant because adding a poorly measured omitted variable is not helpful. Consider the intermediate case, where $\sigma_v^2 \approx k$, and suppose for expositional purposes $\sigma_v^2 \approx \sigma_{Eg}^2$, then $plim[\delta^{**} - \delta^{*}] = -\frac{\rho_{Val,Eg}\sigma_{Eg}}{\sigma_{Val}}\gamma\frac{1-\rho_{Val,Eg}^{2}}{2-\rho_{Val,Eg}^{2}}$. The first term gets large as $\rho_{V,Eg}$ becomes more negative, while the third term gets small. In other words, there are two effects. On the one hand, measurement error matters because it tells the researcher whether adding the omitted variable helps. On the other hand, whether measurement error comes in depends on $\rho_{V,Eg}$. For higher absolute value of $\rho_{V,Eg}$, the measurement error is more important, which means the biases are similar and spreads are smaller. Thus, a small measurement error can still cause a problem due to this contemporaneous correlation. These two effects offset but illustrate the importance of $\rho_{V,Eg}$ in uncovering *value*'s ability to forecast expected returns. If this correlation varies through time, equation (5) suggests there may be some periods when *value* forecasts expected returns better than in other periods.

C. The Role of Momentum

Regression equation (3) requires a measure for expected future cash flow growth. A possible proxy for future earnings growth is embedded in stock prices, which we estimate using a firm's recent equity return performance (i.e., *momentum*). Positive or negative shocks about a company's growth prospects will impact stock prices immediately even though their impact on realized earnings growth might not be observed until later. While m*omentum* may not explain the level of growth rates per se, it can forecast *changes* in future growth rates. Starting with Beaver, Lambert, and Morse (1980), there is an extensive accounting linking stock returns to future earnings growth.[6] More generally, there is a long history in finance on the relationship between returns and future fundamentals, including investigations of the Campbell and Shiller (1988) present value model, as well as the price informativeness literature.[7]

Motivated by this literature, we replace $E_t[g_{CF_{it\infty}}]$ with the forecast, $\hat{g}_{CF_{it}} = f(R_{it-J,t})$ in equation (3). Given the measurement error discussion in Section II.B, we can write price *momentum* in terms of expected future growth, that is, $E_t[g_{CF_{it\infty}}] + v_{it+1} = \hat{g}_{CF_{it}} = f(R_{it,t-J})$, which we rewrite as $R_{it,t-J} = \mu_i + \varphi E_t[g_{CF_{it\infty}}] + v_{it+1}$. Substituting $Mom_{it} \equiv R_{it,t-J}$ for $E_t[g_{CF_{it\infty}}]$ in equation (3):

$$R_{it+1} = \alpha + \gamma \tfrac{1}{\varphi} Mom_{it} + \delta Val_{it} + \varepsilon_{it+1} \qquad (7)$$

Unlike cross-sectional regression equation (3), equation (7) is a feasible regression equation because it replaces future expected growth with return *momentum*, which can be observed ex ante. In equation (7), *value* and *momentum* go hand-in-hand. *Momentum* does not have to be its own factor or anomaly, but rather is simply the variable that helps the researcher extract expected returns out of the *value* variable. If the present value model is a reasonable first order approximation of reality and return momentum forecasts future earnings growth, then *momentum* and *value* together will better explain expected returns. Of course, the coefficient estimators in equation (7) are governed by the omitted variables and measurement biases of equations (4) and (5), which can make inference challenging.

To this point, equations (4) – (6) describe the impact of omitted variables and measurement error on the *value* coefficient, δ, in regression equation (3). Here, assuming the present value model in equation (2), we apply a similar analysis for the regression in equation (7), focusing on the *momentum* coefficient, γ. Specifically, running a univariate cross-sectional regression of realized returns on *momentum*, the coefficient on *momentum* is:

[6] Beaver, Lambert and Ryan (1987), Collins, Kothari and Rayburn (1987), Freeman (1987), Collins and Kothari (1989), Kothari (1992), Kothari and Sloan (1992), Liu and Thomas (2000), and the survey by Dechow, Zha and Sloan (2014).

[7] See, for example, Morck, Yeung and Yu (2000), Durnev, Morck, Yeung and Zarowin (2003), Chen, Goldstein and Jiang (2007), Bonds, Edmans and Goldstein (2012), Chen, Da and Zhao (2013), Bai, Philippon and Savov (2016), David, Hopenhayn, and Venkateswaran (2016), and Davila and Parlatore (2018).

$$\text{plim}\left[\gamma^*\right] = \frac{\gamma\sigma_{Eg}^2 + \delta\,\text{cov}\left(Val, Eg\right)}{\sigma_{Eg}^2 + \frac{\sigma_v^2}{\varphi^2}}$$

$$= \gamma\frac{\sigma_{Eg}^2}{\sigma_{Eg}^2 + \frac{\sigma_v^2}{\varphi^2}} + \delta\frac{\rho_{Val,Eg}\sigma_{Val}\sigma_{Eg}}{\sigma_{Eg}^2 + \frac{\sigma_v^2}{\varphi^2}} \tag{8}$$

$$= \frac{\sigma_{Eg}\sigma_R\rho_{Eg,R}}{\sigma_{Eg}^2 + \frac{\sigma_v^2}{\varphi^2}}$$

The last line derives from substituting in the values, $\gamma = \frac{\sigma_R\rho_{R,Eg}}{\sigma_{Eg}\left(1-\rho_{V,Eg}^2\right)} - \frac{\sigma_R\rho_{R,V}\rho_{V,Eg}}{\sigma_{Eg}\left(1-\rho_{V,Eg}^2\right)}$ and $\delta = \frac{\sigma_R\rho_{R,V}}{\sigma_{VAL}\left(1-\rho_{V,Eg}^2\right)} - \frac{\sigma_R\rho_{R,Eg}\rho_{V,Eg}}{\sigma_{VAL}\left(1-\rho_{V,Eg}^2\right)}$. Several observations are in order. First, and notably, γ^* will still be positive as long as a firm's return is cross-sectionally correlated to a firm's future expected earnings growth (i.e., $\rho_{Eg,R} > 0$). This result has nothing per se to do with typical explanations in the finance literature for *momentum*, but rather is a direct consequence of the present value model.[8] Expected returns, whether driven by risk or behavioral biases, should be described by *value* and price *momentum* together. Second, the cross-sectional *momentum* coefficient γ^* will be a downward biased estimate of the true coefficient on expected growth described in equations (2) and (3). There are two effects reducing *momentum's* coefficient: (i) *momentum* is an imperfect proxy for expected future growth, and (ii) *momentum* is likely negatively correlated with the omitted variable, i.e., *value*, given that *value* has a positive relation with returns (i.e., $\delta > 0$).

What happens to these conclusions when the researcher performs a multivariate regression with both *value* and *momentum* as independent variables? The regression coefficient on *momentum* becomes:

[8] This interpretation is cross-sectional in nature. The present value model in theory, however, works for both the cross-section and time-series. In the dynamic version of the GGM, the right combination of a firm's valuation ratio and its expected future growth explains its expected future returns over a given period (see, for example, Johnson (2002) and Liu and Zhang (2008), both providing a rational explanation for momentum linking it to future dividend growth rate). A positive coefficient on *momentum* in a univariate time-series regression necessarily means returns are predictable, and, in a rational framework, the only thing that should predict returns is compensated risk, implying *momentum* is capturing some of this risk. Of course, returns might have even greater predictability using the valuation ratio and other growth information. A likewise explanation, for example, applies to behavioral models with respect to underreaction.

$$\text{plim}\left[\gamma^{**}\right] = \frac{\left(\sigma_{Val}^2\right)\text{cov}\left(R, Eg\right) - \text{cov}\left(Val, Eg\right)\text{cov}\left(R, Val\right)}{\left(\sigma_{Eg}^2 + \frac{\sigma_v^2}{\varphi^2}\right)\sigma_{Val}^2 - \text{cov}\left(Val, Eg\right)^2}$$

$$= \gamma\left(\frac{\sigma_{Eg}^2}{\sigma_{Eg}^2 + \frac{\sigma_v^2}{\varphi^2}\Big/\left(1-\rho_{Val,Eg}^2\right)}\right) \tag{9}$$

The coefficient on *momentum* in the multivariate regression in equation (7), γ^{**}, remains downward biased, either because of high variance of the measurement error, σ_v^2, or little relation between *momentum* and future earnings growth, φ. This bias is also impacted by the correlation of *value* and expected growth, $\rho_{Val,Eg}$, and, in particular, gets worse the higher $\rho_{Val,Eg}$ becomes. That is, even if measurement error σ_v^2 is small, the coefficient on *momentum* may still be biased due to the high contemporaneous correlation between *value* and expected growth.

Interestingly, the coefficient on *momentum* does not necessarily increase as the researcher runs the "correct" multivariate regression with *momentum* and *value* relative to the univariate regression with just *momentum*. Comparing in equation (8) to (9) shows that both coefficients are biased downward due to σ_v^2 and $\rho_{Val,Eg}$, and, for the univariate regression, also due to δ, the coefficient on the omitted variable, *value*. For many parameter values, $\text{plim}\left[\gamma^{**}\right] > \text{plim}\left[\gamma^{*}\right]$, but this will not be true for highly negative $\rho_{Val,Eg}$ and low δ. In contrast, if $\rho_{Val,Eg} = 0$, then the univariate and multivariate regressions are equally biased, i.e., $\gamma > \text{plim}\left[\gamma^{*}\right] = \text{plim}\left[\gamma^{**}\right]$.

The above analysis and that of Section II.B highlight the importance of $\rho_{Val,Eg}$. Negative correlation between *value* and *momentum* is well-documented empirically (Asness, Moskowitz, and Pedersen (2013)). Here, *value* and *momentum* are naturally negatively correlated. High price multiples (i.e., low value) imply high growth or low discount rates (i.e., expected returns). Holding expected returns constant, there is a one-to-one negative mapping between high growth and *value*. If *momentum* is simply a proxy for future expected growth and high future growth increases the stock price, then the relation holds. This point provides a way to understand previous explanations which focus on the mechanical relation between *value* and *momentum*, i.e., winners (losers) are those stocks whose prices have gone up (down), leading to high (low) valuation ratios. One interesting corollary is that the correlation between *value* and *momentum* will vary through time as risk changes and expected returns vary. This correlation is also interesting because, to the extent momentum measures expected future cash flow growth with error, empirical estimates of the *value* and *momentum* effect will vary.

C.1 Value with updated prices

To this point, Asness and Frazzini (2013) argue, and provide supporting evidence, that value measures like book-to-market should use the most recent price to define value. Existing book-to-market measures, as originally constructed by Fama and French (1992), update once per year on June 30 using market and book values as of the prior end-of-year. The present value theory of equation (2) points towards using the most recent price. The most recent price incorporates both future expected cash flow growth and corresponding discount rates, while *momentum* (i.e., stock return news) also potentially forecasts future cash flow growth. Interestingly, this leads to *value* being more negatively correlated to *momentum*, which in turn has econometric implications for the coefficient estimates, as described by equations (4) – (6) and (8) – (9). In addition, to the extent *momentum*'s main role in (7) is capturing recent information shocks about future cash flow growth, it follows that, once *momentum*'s contribution is accounted for, *momentum* should have little forecast power for future returns. The question then becomes whether or not momentum has marginal forecasting power after controlling for its ability to forecast cash flow growth. If other measures such as analyst earnings forecasts or revisions provide equal or better information, then *momentum*'s effect will be diminished. Thinking about *momentum* this way provides a new perspective on the debate about whether *momentum* strategies are profitable.

C.2 Momentum horizon

In addition, a puzzle exists with respect to why *momentum*'s medium-term return horizon seems to work best. (See, for example, Jegadeesh and Titman (1993), Novy-Marx (2012) and Asness, Frazzini, Israel, and Moskowitz (2014).) Under-reaction hypotheses for *momentum* imply a declining autocorrelogram for stock returns – under-reaction to news should have its greatest impact at short horizons, declining thereafter. The present value framework, however, provides a simple explanation for why the medium-term return horizon might be optimal. *Momentum* matters to the extent it forecasts true cash flow growth, and there is no reason why the most recent stock price change has more information about this growth than cumulative stock price changes over the past few months. The ''best'' horizon is the one which contains the most news about future cash flow growth, which will complement the valuation ratios. At shorter horizons (e.g., a day or month) prices likely contain all sorts of other information, including temporary price pressure and liquidity demand effects that obscure information from long-term growth rates. On the other hand, really long horizons capture the cumulation of innovations of future cash flow growth (along with information about discount rates) that at some point reflect growth levels and not just innovations, so long horizon returns likely contain information about both *value* and *momentum*. Indeed, it is quite common practice to choose past long-horizon returns as measures of value (Asness, Moskowitz, and Pedersen (2013)). Hence, the intermediate horizon of 6-12 months may offer a good tradeoff that ameliorates the noise in short-term returns but is also able to capture information about growth innovations, without being contaminated by levels or value. Thus, our present value framework also provides intuition for why *momentum* operates most effectively at intermediate-term horizons.

III. Unified Framework for *Value* and *Momentum*: Empirical Evidence

We provide empirical evidence for evaluation of the unified framework for *value* and *momentum*.

A. Data

We examine three datasets that cover U.S., global, and specifically Japanese stocks. For each firm in these datasets, we collect data on stock returns, past 2-12 month stock returns (price *momentum*), forecasts of next year's earnings growth, realized earnings each year and its most recent book-to-market ratio (*value*). The data is all monthly except for realized earnings growth which is annual. Realized earnings growth measures next year's earnings over the current year. Depending on the month, the growth rate could represent future annual earnings growth measured starting from 13 up to 23 months in the future.[9] For each cross-section in a given period, we include only firms with the above data.[10] The first dataset covers the US Russell 3000 stocks from March 31, 1984 to December 31, 2019 which has good coverage for analysts' forecasts. The second dataset covers MSCI World stocks over a similar period (January 31, 1989 to December 31, 2019). The constituents of the MSCI World index cover approximately 1,650 firms across 23 developed countries (less than half of which are US-based companies) with an average of 1,377 observations per period. In contrast to the Russell 3000, the MSCI index only includes mid and large cap companies. The third dataset covers the constituents of the Japanese MSIC index (August 31, 1988 to December 31, 2019), which are companies traded on the Tokyo Stock Exchange, averaging 274 firms.

[9] In terms of actual measurement, because the annualized earnings are not released until the end of the first quarter, the actual growth rate may not be known until as late as 26 months if time *t* is January of the current year. Note also that if earnings are negative in the current year, we consider the earnings growth the following year to be missing. Of course, if earnings are positive this year and then negative the following year, this would count as negative realized earnings growth. Thus, our analysis describes the cross-section of firms who currently have positive earnings.

[10] Not all regressions require either the earnings forecasts or realized earnings, so some regressions could have a larger cross-section in a given period. However, to make the results comparable across different regressions, we impose the same filter across specifications. Results are largely unaffected by this choice, with one notable exception which we discuss in Section IV.

We run three different specifications. The first is a standard look at the entire cross-section of raw values for all variables. The second specification uses the ranks of these variables to normalize them, and the third specification adjusts the raw values for industry median values to analyze within-industry effects. With respect to the rank regressions, each stock's characteristic is ranked and rescaled to give it an ordinal value from 0 to 1 based on the level of its *momentum*, *value*, forecasted earnings growth and realized earnings growth each period. Cross-sectional rank normalization helps smooth outliers in the data, but provides a less clear economic interpretation than using raw values.[11] For the bulk of the analysis in the paper, we use raw values, but mention where we use ranks for robustness. With respect to industry adjustments, grouping stocks by industry helps adjust for industry level effects across the variables such as *value* and realized earnings. Each stock belongs to one of 60 to 70 industries (depending on the time period) based on its three-digit GICS-code. For each variable at each point in time, we calculate the industry median and subtract it from the raw individual firm value for each variable.

B. Momentum and Future Earnings Growth

If the present value theory provides a unified framework for *value* and *momentum* effects in asset pricing, then *momentum* should forecast future earnings growth. Intuitively, stock price *momentum* (i.e., recent performance) may contain information about future realized earnings growth. Empirically, we test this hypothesis by running a Fama-Macbeth cross-sectional regression of future realized earnings growth on stock price *momentum*. Because the theory links news about future earnings growth embedded in stock returns, we also decompose price *momentum* into earnings and non-earnings seasons.[12] The coefficients are then averaged over time and the corresponding *t*-statistic is calculated in the style of Fama and MacBeth (1973). Because realized earnings growth is annual, we conservatively adjust the standard errors by $\sqrt{12}$ for overlapping observations (Valkanov (2003) and Hjarmlsson (2011)).

Table 1 presents the results. For the raw data with no industry adjustment, this proof-of-concept regression implies price *momentum* forecasts future earnings growth. Consistent with the hypothesis, in regression #1, the coefficient on price *momentum* is 0.0016 with a highly significant *t*-statistic of 5.21. In regression #2, we decompose price *momentum* into earnings and non-earnings seasons using dummy

---

[11] For raw values, we winsorize at the 5% level due to growth rates being volatile when current earnings are close to zero.

[12] Frazzini and Lamont (2007) document earnings announcement month premia, linked by Barber et al (2013) using a sample of stocks in 40 countries, to higher idiosyncratic volatility. Savor and Wilson (2016) further provide evidence that the premium is larger for early season announcers, consistent with fundamental information. Moskowitz (2021) compares firms with recent versus older earnings announcements, finding that for firms with new (old) announcements, *value* (*momentum*) works relatively "better" than *momentum* (*value*). This literature suggests the earnings season may be important. We define the earnings season as the 26 business days of the first quarter of the previous year that had the largest number of earnings announcements, and the 16 business days of each of the other quarters of the previous year, for the current quarter.

variables. Price *momentum* is slightly stronger at predicting earnings growth in earnings seasons. Though both variables are still statistically significant (with *t*-statistics of 4.22), the coefficient on the earnings season *momentum* is 39% higher. The ability of price *momentum* to forecast future earnings growth in the cross-section, and the slightly higher coefficient during earnings season, implies that stock price news has information about shocks to earnings growth. Price *momentum* may not tell us anything, however, about expected earnings growth levels and thus has some limitations as a forecast of future earnings growth.

Regression #3 provides results for a cross-sectional regression of earnings growth on analysts' forecasts of earnings. These forecasts, unlike price *momentum*, directly estimate the future one-year earnings growth and are focused on the level of earnings growth, not just changes. Analyst forecast growth comes in strong and significant, with a coefficient of 0.2244 (*t*-statistic of 3.87). The R^2 using analysts forecast growth is also somewhat higher than using price *momentum* (4.3% versus 1.2%). The strong results for analysts forecast growth are consistent with the accounting literature (Bradshaw et al. (2012), Easterwood and Nutt (1999), among others).

Finally, regression #4 presents results for multivariate regressions of realized earnings growth on both *momentum* and analyst's growth forecasts. The coefficient on price *momentum* increases slightly to 0.0017 and its *t*-statistic rises to 5.93. Hence, controlling for the level of growth, as forecasted by analysts, price momentum seems to capture realized changes in growth across stocks more reliably. On the flip side, the precision of the analyst's earnings forecast coefficient also improves when controlling for *momentum*, with the coefficient increasing to 0.24 (*t*-statistic of 4.27). These results indicate that price *momentum* has information about future growth that is independent from analysts' forecasts. This result may seem surprising given that analysts also have access to stock price returns when making their forecasts. The accounting literature documents that analysts' forecasts are not unbiased or efficient (see Abarbanell (1991), Trueman (1994), Abarbanell and Bushee (1997), and Easterwood and Nutt (1999), among many others, for a discussion of the various biases). Our results regarding *momentum* are nevertheless novel. Taking these results together, our findings suggest that analysts' forecasts might be measuring the level of earnings growth, while price *momentum* may capture the changes in earnings growth. Both, however, contribute significantly to future earnings growth.

One of the issues in using raw values of realized and forecasted earnings growth is that the volatility of these growth measures can be exceedingly high, especially when the denominator (i.e., the level) is close to zero. While winsorization helps, we also report regression results using rank values instead of raw values (regressions #5, #6, and #7). The results are consistent with those described above – both price *momentum* and analyst forecasted earnings growth cross-sectionally predict future earnings growth, and even more so when used together. Moreover, consistent with our robustness discussion, the t-statistics increase dramatically to 9.94 for price *momentum* alone, 12.57 for earnings growth forecasts alone, and 10.78 and 12.92 when combined. While the rest of the paper focuses on the more standard analysis using raw values, these results suggest that rank standardization may improve the precision of these relationships.

The cross-section of stock returns also contains news about discount rates and cash flow shocks, but not necessarily the cross-sectional levels of cash flow growth. To partially account for this issue, we rerun the regressions (#8, #9 and #10 in Table 1) adjusting firm earnings growth by its median industry growth rate. The motivation is that the median industry growth rate captures the level effect for each firm. The results are quite similar to those of regressions #1, #3, and #4. For example, in regression #8, the coefficient on *momentum*, 0.0014, barely changes and is strongly significant with a t-statistic of 5.65.[13]

C. Value, Momentum, and Expected Earnings Growth

In this subsection we present the key results of the paper. We run Fama-Macbeth cross-sectional regressions of the return on a stock on different combinations of each stock's characteristics of price *momentum*, *value*, forecasted earnings growth, and future realized earnings growth. These coefficients are averaged over time and the corresponding t-statistics calculated in the style of Fama and MacBeth (1973). Table 2 documents the results for the Russell 3000 index. We perform the analysis for both raw and industry-adjusted variables.

Before discussing the results, it is worthwhile commenting on including realized future earnings growth on the right-hand side, that is, regressing $R_{it,t+1}$ on $g_{it+j,t+k}$ (where we have dropped the *CF* subscript). Future earnings growth can be broken down into its expected component at future time $t+j$, $E_{t+j}\left[g_{it+j,t+k}\right]$, and its unexpected shock, $\varepsilon_{g_{it+j,t+k}}$. The future expected component $E_{t+j}\left[g_{it+j,t+k}\right]$ itself can be decomposed into its expected growth rate at time t, $E_t\left[g_{it+j,t+k}\right]$, plus changes in expectations of this future growth rate, $\Delta E_{t,t+j}\left[g_{it+j,t+k}\right]$. That is,

$$\begin{aligned} g_{it+j,t+k} &= E_{t+j}\left[g_{it+j,t+k}\right] + \varepsilon_{g_{it+j,t+k}} \\ &= E_t\left[g_{it+j,t+k}\right] + \Delta E_{t,t+j}\left[g_{it+j,t+k}\right] + \varepsilon_{g_{it+j,t+k}} \end{aligned} \qquad (10)$$

[13] *Ex ante*, we might have expected even stronger results. One reason why this may not be the case is that the rank correlation between firms' earnings growth over consecutive periods is surprisingly low. It is difficult, therefore, to adjust for firm's earnings growth levels using coarse industries, which supports the specification using analyst's earnings growth forecasts. We have also investigated empirical models using past earnings growth per firm to adjust for levels. The results are robust to this specification.

It is possible that $R_{it,t+1}$ relates to $g_{it+j,t+k}$ either through the conditional expected stock return, $E_t\left[R_{it,t+1}\right]$, or the unexpected return, $\varepsilon_{it,t+1}$, which correlates respectively with either $E_t\left[g_{it+j,t+k}\right]$ or $\Delta E_{t,t+j}\left[g_{it+j,t+k}\right]$. Note that $E_t\left[R_{it,t+1}\right]$ cannot explain future changes in growth expectations, so price *momentum* and other earnings growth forecasts must enter the return regression equation (7) via $E_t\left[g_{it+j,t+k}\right]$. In contrast, unexpected returns $\varepsilon_{it,t+1}$ can help explain $\Delta E_{t,t+j}\left[g_{it+j,t+k}\right]$ via the one period overlap of changing expectations $\Delta E_{t,t+1}\left[g_{it+j,t+k}\right]$.

Regression #1 of Table 2 presents the results for price *momentum*. The coefficient has the expected positive sign but is insignificant at conventional levels. The coefficient of 0.000024 represents an impact of 2.88% annualized for a one-standard deviation increase in the stock's price *momentum*. This result is weaker than results in the literature for price *momentum*, but it should be noted previous results in the literature rely on a longer sample period and possibly different stock samples that include very small stocks. Theory implies price *momentum* should "work" because, as Table 1 documents, price *momentum* forecasts cross-sectional future earnings growth rates. That said, equation (8), and the discussion in Section II.C, shows that a univariate regression of returns on price *momentum* is underestimated due to measurement error and model misspecification through omission of the valuation ratio.

These results contrast with that of *value* in regression #2. Relative to the coefficient on *momentum*, the coefficient on *value* is 0.004781 and significant with a *t*-statistic of 2.84. Importantly, with respect to the thesis of this paper, when price *momentum* and *value* are combined in a multivariate regression #3, the coefficients on price *momentum* and *value* increase by 75% to 0.000042 for *momentm* and by 40% to 0.006681 for *value*, with *t*-statistics of 1.86 and 4.80, respectively. The key finding of Table 2 – the larger coefficient and improved statistical significance on *value* – is consistent with the theory and the statistical issues outlined in Section II.B.

Value and *momentum* working better together empirically is not a new result. Asness (1997) documents this finding which has been subsequently confirmed in numerous other analyses, including Asness, Moskowitz, and Pedersen (2013) who show it holds across many asset classes. Our interpretation of this result is, however, novel. The higher coefficients on *value* and *momentum* together arise because (i) *momentum* proxies for expected future cash flow growth (see Table 1), and (ii) the present value model (equation (2)) implies value and expected future growth are fundamental components of expected returns. The weaker coefficients in univariate regressions on *value* and *momentum* are theoretically expected due to omitted variables bias (see equations (4)-(6) and (8)-(9)).

An implication of our interpretation and model is that if price *momentum* is only a loose proxy for future expected cash flow growth, then using better proxies for expected future cash flow growth should have an even stronger effect on *value's* ability to predict returns. Regression #4 of Table 2 investigates this conjecture directly. We run a multivariate Fama-Macbeth cross-sectional regression of stock returns on price *momentum* and *value*, but now also include realized future earnings growth (over the next year as described in footnote 8). If our explanation is correct, price *momentum* and realized earnings growth both proxy for future expected earnings growth. As discussed above, because realized earnings growth is by construction made up of current expected future earnings growth plus unexpected future changes, it is logical that realized earnings growth is a better proxy than price *momentum*. Table 2 confirms this implication. The coefficient on price *momentum* drops 38% and is insignificantly different from zero (*t*-statistic of 1.16). In other words, realized earnings growth drowns out price *momentum*'s effect. In contrast, the coefficient on future realized earnings growth is 0.011791 with a *t*-statistic of 19.25. Note that there is no mechanical overlap between returns, $R_{it,t+1}$, and future earnings growth, $g_{it+j,t+k}$, only to the extent expected future earnings growth incorporates prior changes in earnings growth from $g_{it,t+1}$. Finally, and most importantly, while the coefficient on *momentum* drops, the coefficient on *value* significantly increases to 0.007317 with a *t*-statistic of 5.36. These findings are consistent with the present value model and our theoretical interpretation of *momentum*.

D. Variation in the Value-Momentum Relation

The analysis of equations (4)-(6) in Section II.B highlights the interaction of omitted variables, measurement error of expected future growth, and the magnitude of the negative correlation between *value* and *momentum*. An implication of this analysis is that the ability of *value* and *momentum* together to predict returns should be stronger when *value* and *momentum* are more negatively correlated, since *momentum's* ability to clean up *value* in the present value formula is more powerful when the two are more negatively correlated. To investigate this implication, we take the time-series of coefficients on *value* from the Fama-MacBeth regressions, with and without *momentum*. From the results in Table 2, the average coefficient on *value* is 0.004781 without *momentum* and 0.007317 with *momentum* in the regression. The difference between them – 0.0019 (with *t*-statistic 2.78) – is significant. We then take the time-series of this difference period-by-period and relate it to the period-by-period cross-sectional correlation between stock *value* and *momentum*.[14] Over the same sample period, the average cross-sectional correlation of *value* and *momentum* is -0.31. The time-series correlation between the increase in *value's* coefficient with the inclusion of *momentum*, representing its ability to forecast returns, and the cross-sectional *value-momentum* correlation is -0.113, consistent with *momentum* being better able to improve *value's* ability

[14] The results are described here but not shown in any tables or figures. They are available upon request.

to forecast expected returns when it is more negatively correlated to *value*. Thus, in periods when the correlation between *value* and *momentum* is more negative, the coefficient on *value* increases more when *momentum* is included in the regression. As equation (6) implies, this finding depends on the degree of measurement error of expected growth.

In addition, equation (6) implies that the measurement error of expected growth proxies reduces the coefficient on *value*. Repeating the same exercise using future realized earnings growth in place of momentum, the time-series correlation between the improvement in value and the value-momentum cross-sectional correlation is -0.135. The slightly greater negative correlation for realized earnings growth than *momentum* is consistent with this implication. Our findings support the idea that *value* and expected growth measures will uncover expected returns with varying success depending on the strength of the *value-momentum* negative correlation, consistent with theory.

Since *momentum's* role in explaining stock returns is as a proxy for expected earnings growth, we can further examine when it is a better proxy – and hence better return predictor – using earnings seasons. Table 1 provided evidence of stronger price *momentum* during earnings season. In Table 2, return regressions #8 – #10, test this idea further by re-running regressions #1 and #3, decomposing price *momentum* into earnings and non-earnings seasons. The coefficient on *momentum* during earnings season is much higher, 0.000054 (with *t*-statistic 1.90) in regression #8, compared to the much lower coefficient during non-earnings season, 0.000013 (with *t*-statistic 0.53) in regression #9. Moreover, when *value* and the two seasonal *momentum*s are included together in regression #10, both the coefficient on *value* and earnings season *momentum* increase relative to their individual regressions, respectively 0.007171 (with *t*-statistic 4.90) and 0.000063 (with *t*-statistic 2.29). These latter results are consistent with earnings season *momentum* being an improved proxy for earnings growth and consistent with the corresponding econometric analysis of omitted variables and measurement error in Section II. B and II.C.

The results in Table 1 also show that additional variables beyond price *momentum* (e.g., analysts' earnings growth forecasts) explain future earnings growth. In return regressions #5, #6 and #7 of Table 2, we add analysts' forecasts. In regression #5, including analysts' forecasts as the only independent variable, the coefficient is 0.005777 with a *t*-statistic of 2.56. The positive coefficient on earning growth forecasts is consistent with equation (8). In regression #6, we rerun regression #3 with *value* and *momentum*, but now also add analysts' forecast growth. The coefficients on all three measures are statistically significant, supporting the present value model. That said, the coefficients in regression #6 are not any higher than those of regression #3 or #5, which might have been expected based on the econometric analysis of Section II.B and II.C. In addition, analogous to regression #4, when we add realized earnings growth to the regression with *momentum*, *value,* and growth forecasts in regression #7, the coefficients on *momentum* and growth forecasts drop and the coefficient on *value* rises. Importantly, the expected growth proxies are no longer statistically significant, with *t*-statistics of 1.41 for *momentum* and 1.64 for analyst forecasts, providing additional evidence that the measures are proxies for future growth, because realized future earnings growth subsumes them.

The regression results focus on the cross-section of raw returns. As described in Section III.A, it might make sense to adjust cross-sectional growth rates by industry to better capture level effects. We reproduce the results for regressions #1 to #7, adjusting all cross-sectional variables by their median industry value. The results are reported in Table 2 for rows #11 to #17, where the coefficients are slightly higher on *value* and *momentum* with much higher precision and statistical significance, due to the reduction in noise through the industry adjustment.

E. Alternative Measures of Value

In this subsection, we extend the analysis of Table 2 to include different measures of *value*. As shown in Section II.B and II.C, measurement error can have important effects on the properties of the coefficients in a multivariate regression of expected returns on *value* and *momentum*. That section focused on measurement error of expected growth. Here, we focus on measurement error of valuation and consider two alternative measures of *value*. First, the common choice for *value* by researchers uses the book value of equity of a firm relative to its market value (price times shares outstanding). However, several recent papers suggest that book values for firms need to be adjusted to better capture valuation. One adjustment that several studies advocate is to account for intangible assets (e.g., see Penman (2009), Gu and Lev (2017), Peters and Taylor (2017), Park (2019) and Eisfeldt, Kim, and Papanikolaou (2020)). Second, the practical implementation of the theory embedded in equations (2) and (3) is arguably best suited to valuation models based on earnings/price ratios. Of course, which earnings number – current earnings, past moving average of earnings (to minimize noise) or forward earnings (via analysts' forecast) is a research question in its own right. Here, we use the most recent net income number, excluding negative values, but the results are similar using other measures of earnings.

We examine these alternative *value* measures to see if they provide a cleaner measure of expected returns when combined with *momentum.* Table 3A and Table 3B reports the results, respectively, for R&D-adjusted *value* and the alternative E/P measure. With respect to R&D-adjusted *value*, the results closely mirror those of Table 2. The coefficient magnitudes are similar with elevated *t*-statistics. For example, the *t*-statistic on *value* in the univariate regression jumps from 2.84 to 3.88, and on *momentum* and *value* together from 1.86 and 4.80, respectively, to 2.34 and 6.56. When realized earnings growth is added to the regression, the *t*-statistic on *value* increases from 5.36 to 7.41, with *momentum* still being drowned out. These findings are consistent with the literature supporting adjustments to book value as a more precise valuation measure. With respect to earnings/price ratios, the *t*-statistic on *value* alone is 1.53, and while it rises to 3.07 when including *momentum*, the *t*-statistic on *momentum* rises only slightly from 0.96 to 1.33. While cash flow/price ratios may be more suited to the theory, the noise associated with earnings dulls the impact of these ratios relative to the more stable book/market ratios. We find that these alternative measures of *value* are naturally interpreted by our framework, and are consistent with the present value formula and a cleaner valuation measure.

F. *Out of Sample Tests*

For out of sample robustness, we examine (i) global firms, (ii) Japanese firms, and (iii) industries.

(i) International evidence.

We examine the constituents of the MSCI World index over a similar sample period, from January 1989 to December 2019, covering approximately 1,650 firms across 23 developed countries. The index only includes mid and large cap companies. We show that our unified framework explains well why *value* and *momentum* exist in other markets, finding similar evidence across these 23 developed equity markets.

Table 4A repeats the empirical analysis of Table 1 for the global constituent firms of the MSCI World index. The results are similar. The coefficient on *momentum* is 0.0018 (with *t*-statistic 3.72) in the univariate regression which is similar in magnitude and significance to Table 1. Analyst forecast growth also comes in strong with a *t*-statistic of 5.82, and, most importantly, when combined together, both *momentum* and analysts' forecast growth contain independent information. These results mirror those of Table 1 for the Russell 3000.

Table 5A reports the same set of regressions as Table 2 for global stocks, yielding similar results. Price *momentum* on its own does not explain the cross-section of international stocks reliably (coefficient of 0.000034 with a *t*-statistic of 0.91). *Value* on its own reliably prices the cross-section with a coefficient of 0.0035 (*t*-statistic of 2.20). However, when both *value* and *momentum* are included in the regression, both of their coefficients increase in magnitude and statistical significance. *Momentum* has a coefficient of 0.000045 (*t*-statistic = 1.26) and *value* has a coefficient of 0.0044 (*t*-statistic = 3.27). Moreover, when controlling for future realized earnings growth, the effect of *momentum* is subsumed (dropping to 0.000023 with a *t*-statistic of 0.68) and *value's* coefficient increases further to 0.0053 (*t*-statistic = 3.97).

These results corroborate the evidence in the U.S. and provide support for the present value interpretation of *value* and *momentum* effects in 23 other markets.

(ii) Japan

Our framework for understanding *value* and *momentum* effects is potentially useful even in markets where one of those effects appears not to work. Previous research documents weak to non-existent evidence of *momentum* in Japan (Rouwenhorst (1998), Griffin, Ji, and Martin (2003), Chui, Titman, and Wei (2010), Asness (2011), Asness, Moskowitz, and Pedersen (2013), Fama and French (2012)), suggesting that the *momentum* factor is not a useful asset pricing factor in this market. Our third dataset covers Japanese stocks over roughly the same sample period August 1988 to December 2019 from the MSCI index. Consistent with our framework, we show that including *momentum* with *value* in Japan improves valuation measures that exhibit an even stronger link to expected returns. Thus, *momentum* strengthens the link between *value* and expected returns in Japan in a similar fashion as it does in other markets. In other words, looking through the lens of the present value model, *momentum* works in Japan just like it does in every other country around the world – it helps clarify the link between valuation and expected returns as a proxy for earnings growth.

Table 4B documents that the coefficient on *momentum* is significant with a *t*-statistic of 2.61, but the coefficient on analysts' forecasts is insignificant with a *t*-statistic of 0.66. Table 5B confirms the well-documented result that *momentum* alone does not explain the cross-section of stock returns in Japan, with a coefficient of -0.000034 (with *t*-statistic -0.62). This particularly weak result contrasts with the ability of *momentum* to forecast earnings growth in Japan. The result is even more puzzling when Table 5B shows that analysts' growth forecasts help explain the cross-section of stock returns even though in Table 4B there is not a strong relation between these forecasts and future earnings growth. While this point deserves future scrutiny, the econometric equations given in equations (8) and (9) demonstrate how these results could arise due to the size of the measurement error in different earnings growth predictions and the correlation between *value* and the expected growth measures. However, the core result that both coefficients on *momentum* and *value* increase, and realized earnings growth further drowns out *momentum*, are all present in Japan, consistent our previous results in other markets and our interpretation of these findings through the present value formula.

The combination of *value* and *momentum* is a better description of expected returns, even when one of those effects (in this case *momentum*) appears to have little efficacy itself. The results showcase that *value* and *momentum* should be thought of simultaneously, with the present value formula providing a link between them, where *momentum* proxies for expected growth that makes *value* a stronger predictor.

(iii) Industries

Some of our analysis examines individual equities within industries, neutralizing the variation across sectors in terms of accounting, growth prospects, etc., in order to obtain more precise estimates of *value* at the firm level. In this subsection, we focus exclusively on the variation across industries. The present value framework should also apply to industry portfolios, where *value* and *momentum* effects have also been studied (Asness, Porter, and Stevens (2000), Cohen and Polk (1998), Moskowitz and Grinblatt (1999)). This interpretation is especially worth studying because it is well-documented in this literature that *value* effects do not seem to work well at the industry level, while *momentum* effects do. The industry portfolio returns are constructed from the Russell 3000 sample (constructed from up to 60 sectors), and the data sample is monthly over the period March 1984 to December 2019.

Table 4C reports the results for industry portfolios, which mirror those of Table 1. There are statistically significant coefficients on *momentum* and analysts' forecasts, and, when combined, they both provide additional cross-sectional explanatory power for earnings growth. Table 5C mirrors the analysis of Table 2. Consistent with the existing literature on industry portfolios, *momentum* alone comes in significantly with a *t*-statistic of 2.28, whereas the coefficient on *value* is negative (-0.0009) with a *t*-statistic of -0.30. This finding is considered to be somewhat of a puzzle in the expansive literature on *value* and *momentum*. When *value* and *momentum* are combined, however, the coefficient on *value* flips sign and increases to 0.0032 with a *t*-statistic of 1.17. When realized earnings growth is added to the regression, the coefficient and *t*-statistic on *momentum* drop (i.e., respectively from 0.000089 to 0.000067 and 2.11 to 1.63), while the coefficients and *t*-statistics on *value* increase, respectively, to 0.0059 and 1.50.

These results are consistent with those for individual stocks and highlight that even when one of the characteristics – in this case *value* – does not on its own seem related to average returns, when it is combined with *momentum*, we find a stronger connection to expected returns, as the present value theory predicts. *Momentum* provides a proxy for expected growth at the industry level, providing a novel interpretation of industry *momentum* (Moskowitz and Grinblatt (1999)), and enhances the relation between industry *value* and expected returns. Moreover, without an adjustment for industry *momentum*, industry *value* does not explain industry returns, providing an explanation for the previously documented weak relation between *value* and average returns at the industry level (Asness, Porter, and Stevens (2000), Cohen and Polk (1998)).

IV. Asset Pricing Implications for *Value* and *Momentum*

Note that equation (2) does not link conditional expected returns to underlying risk factors, since that requires an asset pricing model. Consider a stock that pays dividends, D_{it}. In this case, the fundamental theorem of asset pricing of Harrison and Kreps (1979) and Hansen and Richard (1987) can be represented by $P_{it} = E_t[M_{t+1}(P_{it+1} + D_{it})]$, or through forward iteration, $P_{it} = \sum_{j=0}^{\infty} E_t[M_{t+1+j}D_{it+j}]$, where M_{t+1} is the equilibrium stochastic discount factor. Rearranging this pricing equation,

$$\frac{P_{it}}{D_{it}} \equiv (Val_{it})^{-1} = \sum_{j=0}^{\infty} R_{f,t,t+j}^{-1} g_{D_{i,t,t+j}} + \sum_{j=0}^{\infty} cov_t\left(M_{t+1+j}, g_{D_{i,t,t+j}}\right) \tag{11}$$

where $g_{D_{i,t,t+j}} = E_t\left[\frac{D_{it+j}}{D_{it}}\right]$, the expected growth rate of j-period dividends, and $R_{f,t,t+j} = \frac{1}{E_t[M_{t+1+j}]]}$, the equilibrium risk-free rate from *t* to *t+j*.

Equations (2) and (11) are quite similar. Like equation (2) for expected returns, equation (11) implies that $\sum_{j=0}^{\infty} cov_t\left(M_{t+1+j}, g_{D_{i,t,t+j}}\right)$ can be uncovered by a stock's valuation ratio adjusted for future expected cash flow growth. The conditional covariance between future dividend growth and marginal rates of substitution maps directly to the risk-premium for stocks (see Cochrane (2001) for a discussion of this equivalence). High negative covariances imply high risk premiums and low valuation ratios. The point is that $\sum_{j=0}^{\infty} cov_t\left(M_{t+1+j}, g_{D_{i,t,t+j}}\right)$ determines expected returns, not Val_{it} or $g_{D_{i,t,t+j}}$, although Val_{it} and $g_{D_{i,t,t+j}}$can be used to uncover $\sum_{j=0}^{\infty} cov_t\left(M_{t+1+j}, g_{D_{i,t,t+j}}\right)$.

As implied by equation (2), the dynamic version of the GGM (e.g., Campbell and Shiller (1988)) – relating expected stock returns on stock *i* to its *value* and m*omentum* measure – is not inconsistent with the conditional CAPM. Indeed, assuming the conditional CAPM holds and following Polk, Thompson, and Vuolteenaho (2008), equation (7) can be rewritten as:

$$E_t[R_{it+1}] - R_{ft} \approx \beta_{it}\left(E_t[R_{mt+1}] - R_{ft}\right) \approx k_i^{**} + \left(\delta_i Val_{it} + \gamma_i Mom_{it,J}\right). \tag{12}$$

Because $E_t[R_{mt+1}]$ is constant across stocks, equation (12) implies that the cross-sectional (and time-series) variation of β_{it} will be related to $\delta_i Val_{it} + \gamma_i Mom_{it,J}$. That is, $\delta_i Val_{it} + \gamma_i Mom_{it,J}$ has a time-varying component that is common across stocks ($E_t[R_{mt+1}] - R_{ft}$), but any cross-sectional variation necessarily relates to its conditional beta, β_{it}. Over the last three decades, researchers have used multi-factor models, such as Fama and French (1992, 1993, 2015), Carhart (1997), and Hou, Xue, and Zhang (2015), among others, to regress realized returns on multiple factors, including the market, size, *value*, *momentum*, investment, quality, and low risk factors. Focusing on *value* and *momentum*, we can summarize these empirical descriptions of returns as:

$$R_{it+1} - R_{ft} \approx \alpha_i + \beta_i(R_{mt+1} - R_{ft}) + \delta_i^* R_{Val,t+1} + \gamma_i^* R_{Mom,t+1} + \phi_i^* R_{Z,t+1} + \varepsilon_{i,t+1} \quad (13)$$

where R_{mt+1}, $R_{Val,t+1}$, and $R_{Mom,t+1}$ are the factor returns on the market, *value*, and *momentum* portfolios, and $R_{Z,t+1}$is the return on other factor portfolios unrelated to market, *value*, or *momentum*.

Equation (12) provides a clue for why equation (13) works in practice, and it is *not necessarily* because the conditional CAPM is a poor model for expected returns. Suppose $\beta_{it} = \beta_{i0} + \beta_{i1,t}$ in equation (12), then the true model for realized returns is $R_{it+1} - R_{ft} \approx \alpha_i + (\beta_{i0} + \beta_{i1,t})(E_t[R_{mt+1}] - R_{ft}) + \varepsilon_{i,t+1}$. Even if $\beta_{i1,t}$ and $E_t[R_{mt+1}]$ are uncorrelated, the single factor model, $R_{it+1} - R_{ft} \approx \alpha_i + \beta_i(R_{mt+1} - R_{ft}) + \varepsilon_{i,t+1}$, suffers from an omitted variable bias. Equation (12) implies that this omitted variable *necessarily* varies with the cross-sectional time-varying portion of firm *i*'s *value*, Val_{it} , and *momentum*, Mom_{it}, characteristic at time *t*. If these firm characteristics similarly vary with $\delta_i^* R_{Val,t+1} + \gamma_i^* R_{Mom,t+1}$, then equation (13) is directly related to equation (12), albeit with measurement error. In equation (13), β_i helps pin down the unconditional average return of stock *i* while δ_i^* and γ_i^* capture the cross-sectional time-varying components of expected returns. Of course, the conditional CAPM might be a poor approximation of reality, as a number of researchers have found, and a more appropriate risk model might be a multi-factor version of the conditional CAPM. In this case, equation (13) is still valid but picks up all the time-varying components of the multiple factors as well as the average unconditional return. This interpretation may explain why some researchers find that *momentum* can be partly, if not fully, captured by better measures of conditional risk premia (Kelly, Moskowitz, and Pruitt (2020), Chordia and Shivakumar (2002)).

A. Growth-Adjusted Value Portfolios

We consider three measures of expected future cash flow growth – price *momentum*, forecasted future growth (using price *momentum* and analysts' forecasts) and realized earnings growth over the next period. For each month over the past 5 years, we run a cross-sectional regression of stock returns on our measures of *value* and expected future growth. Specifically, we run

$$R_{it+1} = a + bG_{it} + cVal_{it} + e_{it+1} \quad (13)$$

each period and average the coefficients over the 60-month prior periods, denoted by $\bar{a}, \bar{b}$ and $\bar{c}$ (these are time-varying rolling averages and should be subscripted by *(t-60,t)*, which we omit for ease of notation).

In the simplest form of the GGM in equation (1), the relative weight between *value* and expected growth is $\frac{c}{b+c}=\frac{\lambda_i}{1+\lambda_i}$ where $\lambda_i=(1-p_i)$ and p equals the plowback ratio. When the weight is high, *value* needs to be adjusted for future growth to back out expected returns.

We take these coefficients and substitute them into equation (3) in order to get an *ex ante* expected return estimate, $\bar{c}Val_{it}+\bar{b}G_{it}+\bar{a}$, for each stock each period. We rank the expected returns from lowest to highest and form five quintile portfolios. These quintile portfolios are then combined to create five-meta portfolios of *ex ante* expected returns. Table 6 provides summary statistics for the quintile portfolios using either *momentum*, forecasted growth[15] or realized earnings growth as proxies for expected growth. We consider three candidate single-factor portfolios, the high minus low *momentum*-adjusted *value* portfolio (HML VM), the high minus low forecasted growth-adjusted *value* portfolio (HML VF), and the (infeasible) high minus low realized growth-adjusted *value* portfolio (HML VG).

Table 6A reports results for *momentum*-adjusted *value* quintile portfolios, based on the *ex ante* cross-sectional regression on *value* and *momentum*. The means of the portfolio returns are monotonically increasing from 8.72% to 17.01%. The volatility of the five quintile portfolio returns follow a U-shaped pattern. The high-minus-low factor return of these portfolios (HML VM) is regressed on the market, the Fama-French 3-factor model, and the Fama-French 3-factor model augmented by *momentum*.[16] The alphas are respectively 8.02% (*t*-statistic 3.69), 8.47% (*t*-statistic 4.00), and 0.76% (*t*-statistic 0.48) suggesting the Fama-French 3-factor model cannot explain the cross-section of expected returns implied by the present value model in equation (3). To this point, it is not surprising that the Fama-French 3-factor model with the UMD momentum factor does span our *momentum*-adjusted *value* factor. Interestingly, it only takes one factor here compared to the standard four-factor model.

Table 6B reports results for forecast-adjusted value portfolios. The means of the portfolio returns are similar to those of *momentum* alone, ranging from a low of 8.41% to a high of 18.39%. Given that *momentum* and analysts' forecasts possess different information about earnings growth as shown in Table 1, the regressions of the high-minus-low forecast-adjusted portfolio (HML VF) return on the market, the Fama-French 3-factor model, and the 4-factor model should be telling. Indeed, the alphas are respectively 8.35% (*t*-statistic 4.39), 9.09% (*t*-statistic 5.38) and 3.60% (*t*-statistic 2.60). Not only are the *t*-statistics all higher, but the significant *t*-statistic from the 4-factor model that include *momentum*, points to

[15] Our model for forecasted growth takes two inputs, *momentum* and analysts' earnings forecast. For each input, each period, we create a z-score over the cross-section for each variable, and then add the two z-score inputs together with a 50-50 weight. We choose this approach over an alternative procedure of cross-sectionally regressing earnings growth on the two inputs using a time-series (e.g., using 5-years as with the return regressions) due to the additional loss of data.
[16] The Fama and French factors, as well as UMD, are collected from Ken French's website. The quintile portfolios here are constructed from a smaller universe based on Russell 3000 stocks.

momentum not being sufficient for the present value model, where we use a richer forecast of earnings growth to adjust *value*. These results support the present value interpretation and showcase that a value-adjusted metric is not fully captured by existing asset pricing models and adds incremental information about expected returns outside of those models. Using analyst forecasts to get a better measure of cash flow growth improves *value's* return predictability for the cross-section of stocks, consistent with theory.

Finally, Table 6C reports the analogous regressions for realized growth-adjusted *value* quintile portfolios. These portfolios are not feasible because the stock's growth measure, G_{it}, uses future realized growth, $g_{it+j,t+k}$, unknown at time *t*. These portfolios are economically interesting, however, because $g_{it+j,t+k}$ has information about the stock return from *t* to *t+1*, either through $E_{t+1}[g_{it+j,t+k}]$ in equation (1) or unexpected growth shocks from *t* to *t+1*, $E_{t+1}\left[g_{it+j,t+k}\right] - E_t\left[g_{it+j,t+k}\right]$. In other words, the portfolios have the potential to somewhat capture the true immeasurable expected growth , $E_t[g_{it+j,t+k}]$. However, because of sorting at least partially on unexpected shocks to future growth, $E_{t+1}[g_{it+j,t+k}] - E_t[g_{it+j,t+k}]$, the means of the portfolio returns are much more disperse than those reported in Table 6A and 6B, ranging from -4.42% to 23.09%. Relative to the market, or Fama-French 3 factor model (with and without *momentum*), the alphas are huge and significant, albeit unattainable.

B. A New Factor Portfolio

Motivated by the results above, we consider the three candidate single-factor portfolios, HML VM, HML VF, and the infeasible HML VG, and compare them to the CAPM, Fama-French-3 factor model, and Fama-French model augmented with *momentum*. Our method of comparison is to apply the approach of Barillas and Shanken (2017). Specifically, we run popular candidate factors against these factor models and test whether the alphas are significantly different from zero. We choose seven factors currently used in the literature, all high minus low portfolios sorted on firm characteristics: the Fama and French (2015) factors, CMA (conservative minus aggressive, i.e., the return on stocks with conservative minus aggressive investments), HML (high minus low *value*, i.e., the return on stocks with high minus low book-to-market), RMW (robust minus weak, i.e., the return on stocks with high versus low operating profitability) and SMB (small minus big, i.e., the return on small stocks minus large stocks); the Frazzini and Pedersen (2014) BAB factor (betting against beta, which is the return on leveraged low-beta stocks minus high-beta stocks); the Asness, Frazzini, and Pedersen (2019) factor QMJ (quality minus junk, which is the return on stocks with a high quality index minus those with a low quality index); the momentum factor, UMD (up minus down *momentum*) from Ken French's website.

Table 7 reports the results for these tests. As is well known, the popular factors are mostly significant against the market model, 3-factor Fama-French model, and that model augmented with the *momentum* factor. We now compare how well our *single* factor HML growth adjusted *value* factors fare against these more standard models.

First, consider the HML VM portfolio with its reported alphas and betas in columns 5 and 6 of Table 7. Compared to the market model, the magnitudes of the alphas (and corresponding *t*-statistics) are lower for six of the seven alternative factors. That said, only HML, SMB, and UMD are statistically insignificant with CMA having a *t*-statistic of only 2.00. However, the magnitudes of the alphas (*t*-statistics) are still lower for four (all five) of the five alternative factors compared to the 3 factor Fama-French model, and lower for one (two) of the four alternative factors compared to the 4 factor model. In other words, the one-factor model is competitive with the standard multifactor models, but does not eradicate some of the anomalous findings in the literature.

The next two columns (7 and 8 of Table 7) report results for the growth forecast-adjusted *value* factor (HML VF). The results are more mixed than those of the *momentum*-adjusted *value* factor and surprising in light of the HML VF model's performance shown in Table 6. Specifically, HML VF has alphas with higher *t*-statistics than HML VM for all seven of the alternative factors, though to be fair, the alphas are fairly consistent in magnitude. We also examine the realized growth-adjusted *value* factor (HML VG) that uses realized growth to incorporate a better measure of expected future growth and captures unexpected growth. Here, the results look a little better. BAB, QMJ, and RMW are no longer significant, which suggests a better forecast model for future cash flow growth may be able to explain some of these anomalies, especially those related to the quality and profitability of earnings. In contrast, HML VG seems to fail the Barillas-Shanken test for HML, CMA, and UMD compared to the other models, with HML and CMA switching signs and in a statistically significant way.[17]

Overall, these results support the present value interpretation of *value* and *momentum* effects in asset pricing. A single factor model motivated by theory that captures growth-adjusted *value* performs as well as popular multifactor models in the literature. These results are instructive of the drivers of the seven anomalous factors most commonly referenced in the asset pricing literature. Whether more dynamic versions of the present value model, better proxies for *value*, and better forecasts of expected growth, can

[17] Table 8 helps us explore these findings more deeply by providing the correlation matrix of the market portfolio, the seven anomalous factors and our three growth adjusted *value* factors. The striking result is that the correlation pattern between the anomalous factors and the HML VG portfolio is very different than either the HML VF and HML VM portfolios for almost all the factors. This is further evidenced through their own correlation to each other. HML VF and HML VM are 0.84 correlated, while HML VF and HML VG are 0.10 correlated, and HML VM and HML VG are 0.20 correlated. Of course, HML VG is infeasible and includes not only the "true" expected earnings growth but also unexpected shocks.

move us further in the right direction to price assets better remains an open question. However, the clarity and intuition provided by the present value framework can help guide and interpret new empirical models that capture the cross-section of expected returns.

V. Conclusion

This paper provides a simple unifying framework of *value* and *momentum* effects in asset pricing based on the present value model. The model implies that expected returns can be estimated via valuation ratios adjusted for expected future cash flow growth, where we find that *momentum* is a reasonable proxy for earnings growth in stocks which provides a novel interpretation of the *momentum* factor. Using cash flow growth proxies helps improve *value*'s forecast for expected returns, and importantly, drowns out *momentum's* contribution to expected returns. Motivated by theory, we construct single factor models based on growth-adjusted *value* that span the cross-section of expected returns. We find that this single factor model does well in comparison to popular multifactor models. However, our growth-adjusted *value* factors do not explain all of the popular anomalous factors, which may be a function of finding better valuation and expected growth measures, which we leave for future research.

Asness, Moskowitz and Pedersen (2013) apply their analysis of *value* and *momentum* to not just global equities, but all major asset classes, and claim *value* and *momentum* holds everywhere. This paper suggests a possible explanation for these findings may be based on present value models of asset prices applied to fixed income assets (e.g., Campbell and Shiller (1988)) and exchange rates (e.g., Engel and West (2005)). We hope to explore the present value implications for *value* and *momentum* in these other markets and asset classes in future research.

References

Abarbanell, J., 1991. Do analysts' earnings forecasts incorporate information in prior stock price changes? Journal of Accounting and Economics 14, 147–165.

Abarbanell, J.S. and Bushee, B.J., 1997. Fundamental analysis, future earnings, and stock prices. *Journal of accounting research*, *35*(1), pp.1-24.

Asness, C. S., 1994, "Variables that Explain Stock Returns", Ph.D. Dissertation, University of Chicago.

Asness, C. S., 1997,"The interaction of value and momentum strategies." *Financial Analysts Journal* 53, no. 2: 29-36.

Asness, C. and Frazzini, A., 2013. The devil in HML's details. *The Journal of Portfolio Management*, *39*(4), pp.49-68.

Asness, C.S., Moskowitz, T.J. and Pedersen, L.H., 2013. Value and momentum everywhere. *The Journal of Finance*, *68*(3), pp.929-985.

Asness, C., Frazzini, A., Israel, R. and Moskowitz, T., 2014. Fact, fiction, and momentum investing. *The Journal of Portfolio Management*, *40*(5), pp.75-92.

Asness, C., Frazzini, A., Israel, R. and Moskowitz, T., 2015. Fact, fiction, and value investing. *The Journal of Portfolio Management*, *42*(1), pp.34-52.

Asness, C.S., Frazzini, A. and Pedersen, L.H., 2019. Quality minus junk. *Review of Accounting Studies*, *24*(1), pp.34-112.

Bai, J., Philippon, T. and Savov, A., 2016. Have financial markets become more informative?. *Journal of Financial Economics*, *122*(3), pp.625-654.

Barber, B. M., De George, E. T., Lehavy, R., & Trueman, B., 2013. The earnings announcement premium around the globe. *Journal of Financial Economics*, *108*(1), 118-138.

Barillas, F. and Shanken, J., 2017. Which alpha?. *The Review of Financial Studies*, *30*(4), pp.1316-1338.

Basu, S., 1983. Earnings' yield and the size effect. *Journal of Financial Economics*, *12*, pp.129-156.

Beaver, W., Lambert, R. and Morse, D., 1980. The information content of security prices. *journal of Accounting and Economics*, *2*(1), pp.3-28.

Beaver, W.H., Lambert, R.A. and Ryan, S.G., 1987. The information content of security prices: A second look. *Journal of Accounting and Economics*, *9*(2), pp.139-157.

Binsbergen, V., Jules, H. and Koijen, R.S., 2010. Predictive regressions: A present-value approach. *The Journal of Finance*, *65*(4), pp.1439-1471.

Bond, P., Edmans, A. and Goldstein, I., 2012. The real effects of financial markets. *Annu. Rev. Financ. Econ.*, *4*(1), pp.339-360.

Boudoukh, J., Michaely, R., Richardson, M. and Roberts, M.R., 2007. On the importance of measuring payout yield: Implications for empirical asset pricing. *The Journal of Finance*, *62*(2), pp.877-915.

Bradshaw, Mark T., Michael S. Drake, James N. Myers, and Linda A. Myers, 2012, "A re-examination of analysts' superiority over time-series forecasts of annual earnings." *Review of Accounting Studies* 17, no. 4: 944-968
Brennan, M.J., Chordia, T. and Subrahmanyam, A., 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, *49*(3), pp.345-373.

Brown, Lawrence D., Robert L. Hagerman, Paul A. Griffin, and Mark E. Zmijewski. 1987. "Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings." *Journal of Accounting and Economics* 9, no. 1: 61-87.

Callen, J.L. and Segal, D., 2004. Do accruals drive firm-level stock returns? A variance decomposition analysis. *Journal of accounting Research*, *42*(3), pp.527-560.

Campbell, J.Y. and Shiller, R.J., 1988. The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies*, *1*(3), pp.195-228.

Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of finance*, *52*(1), pp.57-82.

Chan, K., Hameed, A. and Tong, W., 2000. Profitability of momentum strategies in the international equity markets. *Journal of financial and quantitative analysis*, *35*(2), pp.153-172.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, "Momentum strategies," *Journal of Finance* 51, pp 1681–1713.

Chen, L., Da, Z. and Priestly, R., 2012. Dividend Smoothing and Predictability, *Management Science, 58(10), pp. 1834-1853/*

Chen, L., Da, Z. and Zhao, X., 2013. What drives stock price movements?. *The Review of Financial Studies*, *26*(4), pp.841-876.

Chen, Q., Goldstein, I. and Jiang, W., 2007. Price informativeness and investment sensitivity to stock price. *The Review of Financial Studies*, *20*(3), pp.619-650.

Chordia, T. and Shivakumar, L., 2006. Earnings and price momentum. *Journal of financial economics*, *80*(3), pp.627-656.

Cochrane, J.H., 2001. Asset Pricing Princeton. *New Jersey*.

Cohen, R.B., Polk, C. and Vuolteenaho, T., 2003. The value spread. *The Journal of Finance*, *58*(2), pp.609-641.

Collins, D.W. and Kothari, S.P., 1989. An analysis of intertemporal and cross-sectional determinants of earnings response coefficients. *Journal of accounting and economics*, *11*(2-3), pp.143-181.

Collins, D.W., Kothari, S.P. and Rayburn, J.D., 1987. Firm size and the information content of prices with respect to earnings. *Journal of Accounting and Economics*, *9*(2), pp.111-138.

Da, Z., Jagannathan, R. and Shen, J., 2014. *Growth Expectations, Dividend Yields, and Future Stock Returns* (No. w20651). National Bureau of Economic Research.

Daniel, K. and Titman, S., 1997. Evidence on the characteristics of cross sectional variation in stock returns. *the Journal of Finance*, *52*(1), pp.1-33.

David, J.M., Hopenhayn, H.A. and Venkateswaran, V., 2016. Information, misallocation, and aggregate productivity. *The Quarterly Journal of Economics*, *131*(2), pp.943-1005.

Dávila, E. and Parlatore, C., 2018. *Identifying price informativeness* (No. w25210). National Bureau of Economic Research.

Dechow, P.M., Sloan, R.G. and Zha, J., 2014. Stock prices and earnings: A history of research. *Annu. Rev. Financ. Econ.*, *6*(1), pp.343-363.

Durnev, A., Morck, R., Yeung, B. and Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing?. *Journal of Accounting Research*, *41*(5), pp.797-836.

Easterwood, J.C. and Nutt, S.R., 1999. Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism?. *The Journal of Finance*, *54*(5), pp.1777-1797.

Eisfeldt, A. L., Kim, E., & Papanikolaou, D., 2020. *Intangible value* (No. w28056). National Bureau of Economic Research.

Ellahie, Atif, Michael Katz, and Scott A. Richardson. 2020. "Risky value." *Available at SSRN 2325524*.

Engel, C., N.C. Mark and K.D. West , 2007, “Exchange Rate Models Are Not as Bad as You Think” in *NBER Macroeconomics Annual 2007*, Acemoglu, D., Rogoff, K., Woodford, M., eds., University of Chicago Press, 381-441.

Engel, C., and K. D. West, 2005, “Exchange Rates and Fundamentals,” *Journal of Political Economy* 113, 485–517.

Fama, E.F. and French, K.R., 1992. The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), pp.427-465.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), pp.3-56.

Fama, E.F. and French, K.R., 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance*, *51*(1), pp.55-84.

Fama, E.F. and French, K.R., 1998. Value versus growth: The international evidence. *The journal of finance*, *53*(6), pp.1975-1999.

Fama, Eugene F., and Kenneth R. French. 2000. "Forecasting profitability and earnings." *The Journal of Business* 73, no. 2: 161-175.

Fama, E.F., French, K.R., 2006. Profitability, investment and average returns. *Journal of Financial Economics* 82, 491–518.

Fama, E.F. and French, K.R., 2012. Size, value, and momentum in international stock returns. *Journal of financial economics*, *105*(3), pp.457-472.

Fama, E.F. and French, K.R., 2015. A five-factor asset pricing model. *Journal of financial economics*, *116*(1), pp.1-22.

Fisher, Gregg S., Ronnie Shah, and Sheridan Titman, 2016, "Combining value and momentum." *Journal of Investment Management, Forthcoming*, 14, 33-48.

Frazzini, A., & Lamont, O. A., 2007. The earnings announcement premium and trading volume. *NBER working paper*, (w13090).

Frazzini, A. and Pedersen, L.H., 2014. Betting against beta. *Journal of Financial Economics*, *111*(1), pp.1-25.

Freeman, R.N., 1987. The association between accounting earnings and security returns for large and small firms. *Journal of accounting and economics*, *9*(2), pp.195-228.

Golez, B., 2014. Expected returns and dividend growth rates implied by derivative markets. *The Review of Financial Studies*, *27*(3), pp.790-822.

Gordon, M.J., 1959. Dividends, earnings, and stock prices. *The review of economics and statistics*, *41*(2), pp.99-105.

Griffin, J.M., Ji, X. and Martin, J.S., 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance*, *58*(6), pp.2515-2547.

Hansen, L.P. and Richard, S.F., 1987, The role of conditioning information in deducing testable restrictionsimplied by dynamic asset pricing models, *Econometrica* 50(3), 587–614.

Harrison, J.M. and Kreps, D.M., 1979, Martingales and arbitrage in multiperiod securities markets, *Journal of Economic Theory* 20, 381–408.

Hong, H., Lim, T. and Stein, J.C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, *55*(1), pp.265-295.

Hong, H. and Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance*, *54*(6), pp.2143-2184.

Hou, K., Karolyi, G.A. and Kho, B.C., 2011. What factors drive global stock returns?. *The Review of Financial Studies*, *24*(8), pp.2527-2574.

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang. 2019. *Security analysis: An investment perspective*. No. w26060. National Bureau of Economic Research,

Hou, K., M. van Dijk, and Y. Zhang. 2012. "The Implied Cost of Capital: A New approach." Journal of Accounting & Economics 3(3): 504-526.

Hou, K., Xue, C. and Zhang, L., 2015. Digesting anomalies: An investment approach. *The Review of Financial Studies*, *28*(3), pp.650-705.

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), pp.65-91.

Jegadeesh, N. and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance*, *56*(2), pp.699-720.

Johnson, T. C., 2002. Rational momentum effects. *The Journal of Finance*, *57*(2), 585-608.

Koijen, R.S. and Van Nieuwerburgh, S., 2011. Predictability of returns and cash flows. *Annu. Rev. Financ. Econ.*, *3*(1), pp.467-491.

Kothari, S.P., 1992. Price-earnings regressions in the presence of prices leading earnings: Earnings level versus change specifications and alternative deflators. *Journal of Accounting and Economics*, *15*(2-3), pp.173-202.

Kothari, S.P., 2001. Capital markets research in accounting. *Journal of accounting and economics*, *31*(1-3), pp.105-231.

Kothari, S.P. and Sloan, R.G., 1992. Information in prices about future earnings: Implications for earnings response coefficients. *Journal of Accounting and Economics*, *15*(2-3), pp.143-171.

Lee, CMC, and B. Swaminathanm, 2000, "Price momentum and trading volume." *the Journal of Finance* 55, no. 5: 2017-2069.

Li, J., 2017, "Explaining momentum and value simultaneously." *Management Science* 64, no. 9: 4239-4260.

Liu, J. and Thomas, J., 2000. Stock returns and accounting earnings. *Journal of Accounting Research*, *38*(1), pp.71-101.

Liu, L. X., & Zhang, L., 2008. Momentum profits, factor pricing, and macroeconomic risk. *The Review of Financial Studies*, *21*(6), 2417-2448.

Liu, L.X. and Zhang, L., 2014. A neoclassical interpretation of momentum. *Journal of Monetary Economics*, *67*, pp.109-128.

Merton, R.C., 1980. On estimating the expected return on the market: An exploratory investigation. *Journal of financial economics*, *8*(4), pp.323-361.

Miller, M.H. and Modigliani, F., 1961. Dividend policy, growth, and the valuation of shares. *the Journal of Business*, *34*(4), pp.411-433.

Morck, R., Yeung, B. and Yu, W., 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements?. *Journal of financial economics*, *58*(1-2), pp.215-260.

Moskowitz, T.J., 2021. Asset pricing and sports betting. *The Journal of Finance*, *76*(6), pp.3153-3209.

Moskowitz, T.J. and Grinblatt, M., 1999. Do industries explain momentum?. *The Journal of Finance*, *54*(4), pp.1249-1290.

Moskowitz, T.J., Ooi, Y.H. and Pedersen, L.H., 2012. Time series momentum. *Journal of Financial Economics*, *104*(2), pp.228-250.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics*, *108*(1), pp.1-28.

Novy-Marx, R., 2015. Fundamentally, momentum is fundamental momentum (No. w20984). National Bureau of Economic Research.

Ohlson, J.A., 1995. Earnings, book values, and dividends in equity valuation. *Contemporary accounting research*, *11*(2), pp.661-687.

Park, H., 2019. An intangible-adjusted book-to-market ratio still predicts stock returns. *Critical Finance Review*, *25*(1), 207-236.

Penman, Stephen H., Francesco Reggiani, Scott A. Richardson, and Irem Tuna. 2018. "A framework for identifying accounting characteristics for asset pricing models, with an evaluation of book-to-price." *European Financial Management* 24, no. 4: 488-520.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), pp.435-480.

Polk, C., Thompson, S. and Vuolteenaho, T., 2006. Cross-sectional forecasts of the equity premium. *Journal of Financial Economics*, *81*(1), pp.101-141. 2008??

Rouwenhorst, K.G., 1998. International momentum strategies. *The journal of finance*, *53*(1), pp.267-284.

Barr Rosenberg, K.R. and Lanstein, R., 1984. Persuasive evidence of market inefficiency. *Journal of portfolio management*, *11*, pp.9-17.

Sadka, G. and Sadka, R., 2009. Predictability and the earnings–returns relation. *Journal of Financial Economics*, *94*(1), pp.87-106.

Savor, P., & Wilson, M., 2016. Earnings announcements and systematic risk. *The Journal of Finance*, *71*(1), 83-138.

Trueman, B., 1994. Analyst forecasts and herding behavior. *The Review of Financial Studies*, *7*(1), pp.97-124.

Vuolteenaho, T., 2002. What drives firm-level stock returns?. *The Journal of Finance*, *57*(1), pp.233-264.

Welch, I. and Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, *21*(4), pp.1455-1508.

Zhang, L., 2005. The value premium. *The Journal of Finance*, *60*(1), pp.67-103.

Table 1: Proof of Concept – Future Earnings Growth and Price Momentum

Table 1 provides results for a Fama-Macbeth cross-sectional regression of future realized earnings growth on price *momentum* (and analysts' growth forecasts), with the coefficients averaged over time. In terms of timing, the realized earnings growth measures next year's earnings over the current year. Thus, depending on the month, the growth rate could represent future annual earnings growth measured starting 13 to 23 months in the future. Price momentum is the usual definition of the past 2 to 12 month return on the stock, and analysts' growth forecast represents the earnings forecast corresponding to next year's earnings growth. We consider three variations - raw values, rank values and raw values adjusted for the industry's median value. The standard errors are adjusted by $\sqrt{12}$ due to the overlap (e.g., see Valkanov (2003) and Hjarmlsson (2011)). The results are reported for US Russell 3000. The data sample is monthly over the period March, 1984 to December, 2019

US Russell 3000

Regression #	MOM	MOM Earnings season	MOM Non -earnings season	Earnings growth forecast	Avg R^2
Raw No Sector Adj.					
#1	0.0016				0.012
	(5.21)				
#2		0.0018	0.0013		0.014
		(4.22)	(4.22)		
#3				0.2244	0.043
				(3.87)	
#4	0.0017			0.2400	0.054
	(5.93)			(4.27)	
Rank No Sector Adj.					
#5	0.0901				0.011
	(9.94)				
#6				0.1830	0.036
				(12.57)	
#7	0.0932			0.1851	0.047
	(10.78)			(12.92)	
Raw Sector Adj.					
#8	0.0014				0.008
	(5.65)				
#9				0.2373	0.036
				(4.74)	
#10	0.0015			0.2477	0.045
	(6.73)			(5.04)	

Table 2: Cross-Section of Expected Returns: Value, Momentum, and Expected Earnings Growth

Table 2 provides results for a Fama-Macbeth cross-sectional regression of monthly stock returns against different combinations of each stock's characteristics of price *momentum*, *value*, future realized earnings growth and ex ante analysts' growth forecasts, with the coefficients averaged over time and the corresponding *t*-statistic is calculated. The results are reported for the US Russell 3000 stocks. We consider two variations, one on raw values and the other with the values adjusted for the industry's median value. The standard errors are adjusted by $\sqrt{12}$ due to the overlap (e.g., see Valkanov (2003) and Hjarmlsson (2011)). The results are reported for US Russell 3000. The data sample is monthly over the period March, 1984 to December, 2019.

Russell 3000

Regression #	MOM	Value	Realized Earnings Growth	Growth Forecast	MOM earnings season	MOM non earnings season	Avg R^2
Raw No Sector Adj.							
#1	0.000024						0.022
	(0.96)						
#2		0.004781					0.015
		(2.84)					
#3	0.000042	0.006681					0.032
	(1.86)	(4.80)					
#4	0.000026	0.007317	0.011791				0.042
	(1.16)	(5.36)	(19.25)				
#5				0.005777			0.012
				(2.56)			
#6	0.000047	0.006509		0.005631			0.041
	(2.15)	(4.87)		(2.92)			
#7	0.000031	0.007171	0.011417	0.003151			0.051
	(1.41)	(5.49)	(18.32)	(1.64)			
#8					0.000054		0.010
					(1.90)		
#9						0.000013	0.017
						(0.53)	
#10		0.007115			0.000063	0.000020	0.035
		(4.99)			(2.29)	(0.80)	
Raw, Sector Adj.							
#11	0.000014						0.012
	(0.72)						
#12		0.005520					0.007
		(4.77)					
#13	0.000039	0.007309					0.017
	(2.17)	(7.68)					
#14	0.000026	0.008106	0.009952				0.023
	(1.49)	(8.73)	(23.60)				
#15				0.004999			0.005
				(3.68)			
#16	0.000041	0.007000		0.004255			0.022
	(2.35)	(7.56)		(3.39)			
#17	0.000029	0.008018	0.009803	0.001861			0.027
	(1.65)	(8.86)	(22.34)	(1.46)			

Table 3: Cross-Section of Expected Returns: Alternative Measures of Value

Table 3 provides results for a Fama-Macbeth cross-sectional regression of monthly stock returns against different combinations of each stock's characteristics of price *momentum*, *value*, future realized earnings growth and ex ante analysts' growth forecasts, with the coefficients averaged over time and the corresponding *t*-statistic is calculated. The results are reported for the US Russell 3000 stocks. This table differs from Table 2 above by using two different measures of *value*: one adjusts books values for intangible assets in calculating the book/market ratio, and the other uses the most recent net income to calculate an earnings/price ratio. The standard errors are adjusted by $\sqrt{12}$ due to the overlap (e.g., see Valkanov (2003) and Hjarmlsson (2011)). The results are reported for US Russell 3000. The data sample is monthly over the period March, 1984 to December, 2019.

Panel A: R&D-Adjusted Value

Regression #	Price Momentum	Value	Realized Earnings Growth	Growth Forecast	Avg R^2
#1		0.00481			0.013
		(3.88)			
#2	0.000052	0.00647			0.031
	(2.34)	(6.56)			
#3	0.000036	0.00705	0.011976		0.040
	(1.65)	(7.41)	(19.14)		
#4	0.000055	0.00615		0.004894	0.040
	(2.57)	(6.36)		(2.48)	
#5	0.000040	0.00697	0.011409	0.002274	0.049
	(1.87)	(7.48)	(18.24)	(1.16)	

Panel B: E/P

Regression #	Price Momentum	Value	Realized Earnings Growth	Growth Forecast	Avg R^2
#1		0.0205			0.012
		(1.53)			
#2	0.000032	0.03367			0.029
	(1.33)	(3.07)			
#3	0.000018	0.04885	0.011976		0.039
	(0.77)	(4.53)	(19.14)		
#4	0.000044	0.04967		0.007877	0.037
	(1.90)	(5.16)		(4.13)	
#5	0.000028	0.05739	0.011553	0.005647	0.046
	(1.23)	(6.09)	(18.14)	(2.98)	

Table 4: Future Earnings Growth Predictability for Other Stocks

Table 4 provides results for a Fama-Macbeth cross-sectional regression of future realized earnings growth on price *momentum* (and analysts' growth forecasts), with the coefficients averaged over time. The standard errors are adjusted by $\sqrt{12}$ due to the overlap (e.g., see Valkanov (2003) and Hjarmlsson (2011)). The results are reported in Table 4A for global firms that are constituents of the MSCI World index (approximately 1650 firms across 23 developed countries, less than half of which are US-based companies); in Table 4B for Japanese firms separately that are part of the MSCI World index (averaging 250); and in Table 4C industry portfolio returns constructed from the Russell 3000 sample (constructed from up to 60 sectors). The data sample is monthly over respectively the periods January 1989 to December 2019 (MSCI), August 1988 to December 2019 (Japan), and March 1984 to December 2019 (industry portfolios).

Panel A: MSCI World

Regression #	Price Momentum	Analyst Forecast Growth $E_t[G_{it+1}]$	Avg R^2
#1		0.4810	0.065
		(5.82)	
#2	0.0018		0.019
	(3.72)		
#3	0.0018	0.473	0.082
	(4.07)	(5.70)	

Panel B: Japan

Regression #	Price Momentum	Analyst Forecast Growth $E_t[G_{it+1}]$	Avg R^2
#1		0.1645	0.062
		(0.66)	
#2	0.0052		0.023
	(2.61)		
#3	0.0051	0.1577	
	(2.67)	(0.63)	0.082

Panel C: US Industry Level Regression

Regression #	Price Momentum	Analyst Forecast Growth $E_t[G_{it+1}]$	Avg R^2
#1		0.1955	0.096
		(1.98)	
#2	0.0021		0.059
	(3.03)		
#3	0.0019	0.2089	0.146
	(2.94)	(2.19)	

Table 5: Cross-Section of Expected Returns: Other Stocks Markets

Table 5 provides results for a Fama-Macbeth cross-sectional regression of monthly stock returns against different combinations of each stock's characteristics of price *momentum*, *value*, future realized earnings growth and ex ante analysts' growth forecasts, with the coefficients averaged over time and the corresponding *t*-statistic is calculated. The standard errors are adjusted by $\sqrt{12}$ due to the overlap (e.g., see Valkanov (2003) and Hjarmlsson (2011)). The results are reported in Table 5A for global firms that are constituents of the MSCI World index (approximately 1650 firms across 23 developed countries, less than half of which are US-based companies); in Table 5B for Japanese firms separately that are part of the MSCI World index (averaging 250); and in Table 5C industry portfolio returns constructed from the Russell 3000 sample (constructed from up to 60 sectors). The data sample is monthly over respectively the periods January 1989 to December 2019 (MSCI), August 1988 to December 2019 (Japan), and March 1984 to December 2019 (industry portfolios).

Panel A: MSCI World

Regression #	MOM	Value	Realized Earnings Growth	Growth Forecast	Avg. R^2
#1	0.000034				0.033
	(0.91)				
#2		0.00349			0.017
		(2.20)			
#3	0.000045	0.00439			0.045
	(1.26)	(3.27)			
#4	0.000023	0.00525	0.010779		0.055
	(0.68)	(3.97)	(14.97)		
#5				0.003180	0.010
				(1.14)	
#6	0.000046	0.00409		0.001266	0.053
	(1.33)	(3.09)		(0.51)	
#7	0.000025	0.00509	0.010854	-0.00353	0.063
	(0.73)	(3.90)	(14.36)	(-1.38)	

Panel B: Japan

Regression #	MOM	Value	Realized Earnings Growth	Growth Forecast	Avg. R^2
#1	-0.000034				0.052
	(-0.62)				
#2		0.01108			0.034
		(3.61)			
#3	0.000006	0.01129			0.076
	(0.14)	(4.14)			
#4	-0.000008	0.01223	0.004898		0.089
	(-0.91)	(4.36)	(7.39)		
#5				0.009366	0.016
				(2.80)	
#6	0.000011	0.01145		0.009489	0.089
	(0.23)	(4.17)		(3.03)	
#7	-0.000002	0.01231	0.004452	0.009115	0.100
	(-0.04)	(4.34)	(7.19)	(2.98)	

Panel C: Industry Level Regression

Regression #	MOM	Value	Realized Earnings Growth	Growth Forecast	Avg R^2
#1	0.000096 (2.28)				0.089
#2		-0.00093 (-0.30)			0.057
#3	0.000089 (2.11)	0.00320 (1.17)			0.130
#4	0.000067 (1.63)	0.00587 (1.50)	0.018541 (9.98)		0.182
#5				0.00993 (1.91)	0.074
#6	0.000099 (2.44)	0.00327 (1.28)		0.00692 (1.62)	0.185
#7	0.000078 (1.97)	0.00366 (1.47)	0.017539 (9.38)	0.003151 (1.64)	0.232

Table 6: Statistical Properties of Growth-Adjusted Value Portfolios

Table 6 provides summary statistics for growth-adjusted value quintile portfolios using respectively either *momentum* (in Panel 6A), a combination of *momentum* and earnings forecasts (in Panel 6B) or realized earnings growth (in Panel 6C) as proxies for expected growth. These portfolios are constructed based on the *ex ante* cross-sectional regression of returns on *value* and *momentum*, a 50/50 combination of *momentum* and earnings forecasts (based on z-scores) or realized earnings growth. Specifically, for each month over the past 5 years, we run a cross-sectional regression of stock returns on measures of *value* and expected future growth, $R_{it+1} = a + bG_{it} + cVal_{it} + e_{it+1}$, each period and average the coefficients over the 60-month prior periods, denoted by a bar sign. These coefficients are then substituted into equation (3) in order to get an *ex ante* expected return estimate, $\bar{c}Val_{it} + \bar{b}G_{it} + \bar{a}$, for each stock for each period. We rank the expected returns from lowest to highest and form five quintile portfolios. The results are reported for US Russell 3000 over the period march 1984 to December 2019. The provided alphas are relative to the market portfolio, Fama and French 3-factor model and Fama and French 3-factor model, augmented with the momentum, UMD, factor.

Panel A: Momentum-Adjusted Value Portfolios

Portfolio	Mean	Volatility	
Low ER, Q1	8.72%	20.42%	
Q2	10.33%	16.41%	
Q3	10.63%	16.12%	
Q4	12.06%	16.58%	
High ER, Q5	17.01%	21.40%	
	Alpha, Mkt (*t*-stat)	Alpha, FF3 (*t*-stat)	Alpha, FF3+UMD (*t*-stat)
HML (5-1)	8.02% (3.69)	8.47% (4.00)	0.76% (0.48)

Panel B: Forecast Growth-Adjusted Value Portfolios

Portfolio	Mean	Volatility	
Low ER, Q1	8.41%	18.22%	
Q2	9.46%	15.95%	
Q3	10.16%	15.92%	
Q4	12.35%	17.55%	
High ER, Q5	18.39%	22.38%	
	Alpha, Mkt (*t*-stat)	Alpha, FF3 (*t*-stat)	Alpha, FF3+UMD (*t*-stat)
HML (5-1)	8.35% (4.39)	9.09% (5.38)	3.60% (2.60)

Panel C: Realized Growth-Adjusted Value Portfolios

Portfolio	Mean	Volatility	
Low ER, Q1	-4.42%	21.33%	
Q2	6.68%	16.52%	
Q3	13.58%	15.48%	
Q4	19.86%	16.49%	
High ER, Q5	23.09%	20.07%	
	Alpha, Mkt (*t*-stat)	Alpha, FF3 (*t*-stat)	Alpha, FF3+UMD (*t*-stat)
HML (5-1)	13.98% (8.29)	14.38% (12.58)	13.44% (11.49)

Table 7: Barillas-Shanken Tests of Growth-Adjusted *Value* Factors

Table 7 compares three candidate single-factor portfolios, the high minus low *momentum*-adjusted *value* portfolio (denote HML VM), the high minus low combination forecast-adjusted *value* portfolio (denote HML VF) and the (albeit infeasible) high minus low realized growth-adjusted *value* portfolio (denote HML VG) to the single-factor CAPM, Fama-French-3 factor model and Fama-French 3-factor model (with *momentum*). Our method of comparison is to apply the approach of Barillas and Shanken (2017), running popular candidate factors against these factor models and test whether the alphas are significantly different from zero or not. These factors include four presented in Fama and French (2015), CMA (conservative minus aggressive, i.e., the return on stocks with conservative minus aggressive investments), HML (high minus low value, i.e., the return on stocks with high minus low book-to-market), RMW (robust minus weak, i.e., the return on stocks with high versus low operating profitability) and SMB (small minus big, i.e., the return on small stocks minus large stocks); in Frazzini and Pedersen (2014), BAB (betting against beta, i.e., the return on leveraged low-beta stocks minus high-beta stocks); in Asness, Frazzini, and Pedersen (2019), QMJ (quality minus junk, i.e., the return on stocks with a high quality index minus those with a low quality index); and in Carhart (1997), UMD (up minus down momentum, i.e., the return on stocks with positive returns minus negative returns in the past year).

Alphas of Fama&French Factors Versus Growth-Adjusted *Value* Factors

Portfolio	CAPM α	FF3 α	FF3 (+UMD) α	HML VM α	HML VM β	HML VF α	HML VF β	HML VG α	HML VG β
BAB	10.81%	10.61%	5.11%	8.21%	0.13	9.86%	-0.06	4.35%	0.18
	(4.92)	(4.84)	(2.55)	(3.64)	(2.45)	(4.28)	(-1.06)	(1.49)	(2.57)
HML	1.06%			2.56%	-0.19	2.60%	-0.16	-12.9%	0.48
	(0.50)			(1.21)	(-3.90)	(1.20)	(-2.99)	(-4.69)	(7.78)
SMB	-1.15%			-1.07%	0.12	-3.96%	0.39	5.12%	-0.20
	(-0.74)			(-0.67)	(3.44)	(-2.76)	(11.11)	(2.68)	(-4.14)
CMA	4.51%	4.19%	1.42%	2.44%	0.09	2.97%	0.02	-5.64%	0.32
	(3.96)	(4.23)	(1.63)	(2.00)	(3.21)	(2.37)	(0.67)	(-3.89)	(9.32)
RMW	6.49%	5.96%	5.43%	6.01%	-0.11	8.33%	-0.32	-1.84%	0.25
	(4.57)	(4.70)	(4.14)	(4.04)	(-3.12)	(6.03)	(-9.40)	(-0.98)	(5.71)
UMD	8.85%	9.62%		1.51%	0.68	2.39%	0.48	9.56%	-0.09
	(3.39)	(5.32)		(0.68)	(13.47)	(0.94)	(7.65)	(2.75)	(-1.05)
QMJ	8.30%	8.06%	7.91%	6.26%	-0.07	8.83%	-0.31	1.06%	0.17
	(6.96)	(8.18)	(7.75)	(4.22)	(-2.03)	(6.44)	(-9.31)	(0.56)	(3.74)

Table 8: Correlation Matrix of Anomalous Factors and Growth-Adjusted *Value* Factors

Table 8 documents the correlation matrix between the returns on three candidate single-factor portfolios, the high minus low *momentum*-adjusted *value* portfolio (denote HML VM), the high minus low combination forecast-adjusted *value* portfolio (denote HML VF) and the (albeit infeasible) high minus low realized growth-adjusted *value* portfolio (denote HML VG) with factor portfolios that include the five factors presented in Fama and French (2015): CMA (conservative minus aggressive, i.e., the return on stocks with conservative minus aggressive investments), HML (high minus low value, i.e., the return on stocks with high minus low book-to-market), RMW (robust minus weak, i.e., the return on stocks with high versus low operating profitability) and SMB (small minus big, i.e., the return on small stocks minus large stocks); in Frazzini and Pedersen (2014), BAB (betting against beta, i.e., the return on leveraged low-beta stocks minus high-beta stocks); in Asness, Frazzini, and Pedersen (2019), QMJ (quality minus junk, i.e., the return on stocks with a high quality index minus those with a low quality index); and in Carhart (1997), UMD (up minus down momentum, i.e., the return on stocks with positive returns minus negative returns in the past year).

	BAB	**CMA**	**HML**	**MKT**	**QMJ**	**RMW**	**SMB**	**UMD**	**HML VM**	**HML VF**	**HML VG**
BAB	1	0.355	0.089	-0.232	0.289	0.396	-0.119	0.300	-0.053	-0.141	0.127
CMA	0.355	1	0.467	-0.368	0.149	0.209	-0.156	0.041	0.034	0.009	0.422
HML	0.089	0.467	1	-0.009	-0.227	0.129	-0.053	-0.701	-0.147	-0.079	0.362
MKT	-0.232	-0.368	-0.009	1	-0.593	-0.307	0.234	-0.210	0.276	0.340	-0.174
QMJ	0.289	0.149	-0.227	-0.593	1	0.769	-0.508	0.337	-0.421	-0.517	0.183
RMW	0.396	0.209	0.129	-0.307	0.769	1	-0.484	0.058	-0.423	-0.504	0.274
SMB	-0.119	-0.156	-0.053	0.234	-0.508	-0.484	1	-0.099	0.485	0.526	-0.202
UMD	0.300	0.041	-0.701	-0.210	0.336	0.058	-0.099	1	0.356	0.228	-0.052
HML VM	-0.053	0.034	-0.147	0.276	-0.421	-0.425	0.485	0.356	1	0.840	0.195
HML VF	-0.141	0.009	-0.079	0.340	-0.517	-0.504	0.526	0.228	0.840	1	0.096
HML VG	0.127	0.422	0.362	-0.174	0.183	0.274	-0.202	- 0.052	0.195	0.096	1