A five-factor asset pricing model with enhanced factors*

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Abstract

A simple manipulation of the dividend discount model establishes that firms' book-to-market, profitability, and investment are related to their expected returns. This insight motivates the value, profitability, and investment factors in the Fama-French (2015) five-factor model. Yet, variation in book-to-market, profitability, or investment stems not only from differences in expected returns. In this study, we narrow down the variation in these variables that is actually informative about expected returns to construct enhanced versions of the value, profitability, and investment factors. Our enhanced factors exhibit considerably higher Sharpe ratios than the standard factors. Importantly, a five-factor model using our enhanced factors exhibits a much better pricing performance and generates a more upward sloping multivariate security market line than the standard five-factor model. Moreover, we show that our approach either complements or outperforms other recently proposed approaches to improve the Fama-French (2015) factors.

Keywords: Fama-French five-factor model, value factor, profitability factor, investment factor, cash flow shocks

JEL Classification: G12, G14

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1 Introduction

In this study, we propose enhanced versions of the Fama-French (2015) factors. Fama and French (2015) motivate their factors based on a manipulation of the dividend discount model showing that firms' book-to-market, profitability, and investment are related to their expected returns. However, variation in these characteristics does not only stem from differences in expected return. To narrow down the characteristics' variation that is informative about expected returns, we cancel their variation stemming from other sources than differences in expected returns. A five-factor model that uses factors constructed based on the adjusted characteristics substantially improves upon the standard five-factor model. In particular, it exhibits a much better pricing performance and generates a much more upward sloping multivariate security market line. Our enhanced five-factor model is therefore more appropriate for the usual applications of factor models in academia and practice—determining risk-adjusted returns, estimating capital costs, and evaluating investment performance—than the standard Fama-French (2015) five-factor model.

Factor models are ubiquitous in the empirical asset pricing literature. The five-factor model of Fama and French (2015) is arguably the most established factor model in the recent literature. It comprises market, size, value, profitability, and investment factors. While the market factor is motivated by the theory underlying the CAPM, the size factor is motivated by ample empirical evidence that small stocks have higher average returns than big stocks. The value, profitability, and investment factors are motivated by a simple manipulation of the dividend discount model showing that the factors' underlying characteristics—book-to-market, profitability, and investment—are related to expected returns. This insight yields a profound motivation for the value, profitability, and investment factors as risk factors.

Fama and French (2015, 2016) argue that their five-factor model performs reasonable in explaining the cross-section of stock returns. However, several studies (see, e.g., Jegadeesh et al., 2019) find that there is no positive relation between exposures to the factors and returns. Given that the Fama-French (2015) five-factor model fails to satisfy this theoretically predicted risk-return relation, the interpretation of its factors as risk factors is questionable. This failure also calls into question the application of the five-factor model for determining risk-adjusted returns, estimating capital costs, and evaluating investment performance. Specifically, as pointed out by Chen et al. (2020), accounting for exposure to factors that earn positive average returns does not make sense if higher factor exposures are not associated with higher average returns.

We alleviate this shortcoming of the standard Fama-French (2015) five-factor model. To this end, we introduce enhanced versions of the Fama-French (2015) factors that satisfy the theoretical requirement of a positive relation between factor exposures and returns to a much greater extent. They also yield a better pricing performance and exhibit substantially higher Sharpe ratios than the standard factors. These findings are important for at least three reasons. First, factor models are the workhorse approach in empirical asset pricing. Inferences drawn from applying a factor model such as the Fama-French (2015) five-factor model that is far from satisfying theoretical requirements are highly suspective. This issue is particularly relevant given that the Fama-French (2015) five-factor model is arguably the leading factor model in academia and practice. By contrast, inferences drawn from applying our enhanced factor model are much more reliable as it adheres much more to the theoretical requirement of generating an upward sloping multivariate security market line. Second, our results deliver important guidelines on how to construct theoretically motivated factors. In particular, we show that factors based on characteristics that are, theoretically and empirically, related to expected returns may be improved by narrowing down the characteristics' variation that is actually informative about expected returns. Third, investment strategies based on factors are widely employed in the investment management industry, and the Fama-French (2015) factors are among the most targeted ones. Amid the high Sharpe ratios of our factors, our results yield valuable insights on how the risk-return trade-off of such factor investing strategies can be improved.

Our approach to improve the factors is motivated by recognizing that Fama and French's (2015) construction methodology for the value, profitability, and investment factors neglects a subtle but important aspect: the variation in any of book-to-market, profitability, and investment reflects not only differences in firms' expected returns but also differences in firms' future prospects. Based on this insight, we hypothesize that factors built from book-to-market, profitability, and investment that are adjusted to primarily reflect differences in expected returns rather than future prospects capture more pricing information than the standard Fama-French (2015) factors built from the unadjusted characteristics.

For this purpose, we narrow down the variation in book-to-market, profitability, and investment that is informative about expected returns by canceling their variation that is uninformative about expected returns. First, higher book-to-market is an indicator for higher expected returns because low market equity relative to book equity indicates that future dividends are discounted at a higher discount rate, implying in equilibrium higher expected returns. However, book-to-market may also be high because of an increase in book equity or because of a decrease in market equity stemming from decreased cash flow expectations rather than an increased discount rate. Second, lower investment is an indicator for higher expected returns because low investment indicates that a firm faces high cost of capital, implying in equilibrium higher expected returns. However, investment may also be low because the firm has only few projects with high expected cash flows to invest in. Third, higher profitability is an indicator for higher expected returns because high profitability indicates a firm invested only in very profitable projects due to high cost of capital. However, profitability may also be high because of increased cash flow expectations that make the firm's projects ex-post more profitable than ex-ante expected. We cancel the characteristics' variation that is unrelated to expected returns based on a cash flow shock proxy obtained following Hou and van Dijk (2019).

We construct new versions of the standard Fama-French (2015) size, value, profitability, and investment factors based on the adjusted characteristics. We refer to these new versions as enhanced factors. We document that our enhanced factors in fact substantially improve upon the standard Fama-French (2015) factors. First, they exhibit higher mean returns, lower volatilities, and higher Sharpe ratios than the standard Fama-French (2015) factors. Thus, our adjusted characteristics are more successful in identifying stocks with differential expected returns than the unadjusted characteristics, and they do so more consistently. Thereby, the Sharpe ratio increase is, on average, 50% across the factors.

We show that a five-factor model using our enhanced factors exhibits a considerably and significantly higher maximum Sharpe ratio than the standard Fama-French (2015) five-factor model. Following the arguments of Barillas et al. (2020), the higher maximum Sharpe ratio implies that our enhanced five-factor model gives rise to a better pricing performance than the standard five-factor model. We further document that the Fama-French (2015) factors' pricing information is almost completely captured by our enhanced factors, meaning they contain hardly incremental pricing information beyond our enhanced factors. The opposite does not hold.

Importantly, our enhanced five-factor model comes much closer to satisfying the theoretical predictions that factor exposures should be positively related to expected returns and that the zero-beta rate should be zero than the Fama-French (2015) five-factor model. Specifically, our enhanced model generates an insignificant zero-beta rate and significantly positive risk prices for the market, size, profitability, and investment factors. It only fails to produce a positive risk price for the value factor. By contrast, the Fama-French (2015) model produces a significant zero-beta rate and negative risk prices for the value, profitability, and investment factors. Thus, our enhanced model represents a substantial step forward in generating an upward sloping multivariate security market line.

The recent literature proposed several further procedures to improve the Fama-French (2015) factors. Most noteworthy are the hedging approach of Daniel et al. (2020), the cross-section approach of Fama and French (2020), and the time-series efficiency approach of Ehsani and Linnainmaa (2021). We examine whether our improvement procedure outperforms or complements these procedures. First of all, we find that our enhanced factors have higher individual Sharpe ratios than the factors from these procedures. Moreover, our enhanced model exhibits a higher maximum Sharpe ratio and thus a better pricing performance than the cross-section and time-series efficient model; the hedged model is the only model that can compete with our enhanced model in this regard. Importantly, our enhanced model strongly outperforms the models from the other procedures in generating an upward sloping multivariate security market line. Furthermore, we show that combining our improvement procedure with Daniel et al.'s (2020) hedging procedure yields, in general, further strong improvements; that is, these two procedures complement each other. By contrast, combining our procedure with Fama and French's (2020) cross-section procedure or Ehsani and Linnainmaa's (2021) time-series efficiency procedure does, in general, not lead to further improvements—if anything, applying these two procedures to our enhanced factors harms their performance.

Our study contributes to several strands of literature. First and foremost, it relates to the aforementioned studies suggesting improvement procedures for the Fama-French (2015) factors.

In this regard, our results suggest that narrowing down the variation in the factors' underlying characteristics that is actually informative about expected returns is another promising approach beyond hedging the factors' unpriced sources of variation, optimizing them in the cross-section, and conditioning on their time-series momentum. Our approach differs from these other approaches as we address the factors' underlying characteristics to obtain better factors. By contrast, the other approaches take the original characteristics as given. When comparing our approach to these other approaches, we find that our approach either clearly outperforms the other approaches (the cross-section approach and the time-series efficiency approach) or complements them (the hedging approach).

Furthermore, we contribute to the stream of literature examining the pricing of factor exposures. Studies typically find that the, theoretically, predicted positive relation between factor exposures and returns is, empirically, much weaker than predicted or does not hold at all for many factor models. This has been shown for the CAPM (see, e.g., Black et al., 1972; Fama and French, 1992; Frazzini and Pedersen, 2014), the Fama-French (1993; 1996) three-factor model (see, e.g., Daniel and Titman, 1997), and, importantly, for the Fama-French (2015) five-factor model (see, e.g., Jegadeesh et al., 2019; Daniel et al., 2020). Frequent explanations for the factor models' failure to produce a positive relation between factor exposures and expected returns are that the factors are not true risk factors, that the factors are imperfect proxies for the mean-variance efficient portfolio, and that measurement errors in the betas lead to biased risk premium estimates. Our approach to enhance the factors of the Fama-French (2015) five-factor model by narrowing down their underlying characteristics' predictive information addresses the second explanation.[1] In particular, given their higher individual Sharpe ratios as well as the higher maximum Sharpe ratio of their tangency portfolio, our enhanced factors are better proxies for the mean-variance efficient portfolio than the standard Fama-French (2015) factors. Thereby, to the best of our knowledge, our enhanced five-factor model comes closer to generating an unanimously upward sloping multivariate security market line than any other factor model.

Finally, our study relates to the vast literature documenting the value, profitability, and investment effects in the cross-section of stock returns. Rosenberg et al. (1985) and Fama and French (1992) are among the first to show that book-to-market is positively related to future returns. Novy-Marx (2013) documents that profitability positively predicts future returns. Titman et al. (2004) and Cooper et al. (2008) find that investment is negatively related to future returns. Moreover, numerous studies (see, e.g., Asness and Frazzini, 2013; Ball et al., 2016, 2020; Eisfeldt et al., Forthcoming) suggest alternative versions of the characteristics that are supposed to reflect the effects better than the traditional versions used by Fama and French

[1] We also account for measurement errors in the betas when examining the relation between factor exposures and returns by using the instrumental variables approach of Jegadeesh et al. (2019).

(2015).[2] More similar to us, various studies aim to isolate the variation in the characteristics, in particular in book-to-market, that is informative about future returns. Fama and French (2006) attempt, with limited success, to narrow down book-to-market's predictive power for future returns by canceling its information about expected profitability. Daniel and Titman (2006) split the change in book-to-market into a tangible return and an intangible return, finding only the latter to be informative about future returns. Gerakos and Linnainmaa (2018) decompose the change in book-to-market into book equity changes and market equity changes, showing that book-to-market's predictive power emanates only from market equity changes. We expand on these studies by proposing a method that narrows down book-to-market's, profitability's, and investment's predictive information about future returns successfully respectively more successfully. Thereby, we obtain value, profitability, and investment premia that are considerably stronger than those based on the unadjusted characteristics.

Our findings also have valuable practical implications. Investment strategies based on factors detected in academic studies have been widely adopted in the investment management industry because of their attractive historical risk-return profiles. Our results show how the performance of such factor investing strategies can be further boosted. In particular, given a characteristic that is related to future returns, the risk-return trade-off of a strategy relying on this characteristic can be improved by canceling the characteristics' variation that is unlikely to be informative about future returns. Our findings thereby suggest that the improvements in the risk-return trade-offs do not only emanate from higher average returns but especially also from lower volatilities.

The remainder of the paper is structured as follows: Section 2 motivates our approach to improve the value, profitability, and investment factors. In Section 3, we introduce our data sample, describe our methodology to cancel variation in the characteristics that is uninformative about future returns, and review the construction of the factors. Section 4 presents the properties of our enhanced factors and compares them to the Fama-French (2015) factors. In Section 5, we estimate our enhanced factors' risk prices and compare them to those of the Fama-French (2015) factors. In Section 6, we examine whether our approach to improve the Fama-French (2015) factors complements the approaches of Daniel et al. (2020), Fama and French (2020), and Ehsani and Linnainmaa (2021). Finally, Section 7 concludes.

2 Theoretical Motivation

Fama and French (2015) derive the following relation between a firm's book-to-market, prof-

[2] We stick to the traditional versions of the book-to-market, profitability, and investment characteristics used by Fama and French (2015) to demonstrate our improvement procedure with respect to their factors. Nevertheless, our approach to narrow down the variation in the characteristics that is informative about expected returns can also be applied to alternative versions of the characteristics. Our approach therefore complements rather than rivals the use of the characteristics' alternative versions.

itability, investment, and its expected returns by manipulating the dividend discount model:

$$\frac{M_0}{B_0} = \sum_{t=1}^{\infty} \frac{\frac{E_0(Y_t)}{B_0} - \frac{E_0(dB_t)}{B_0}}{(1+r)^t} \tag{1}$$

where M_0 (B_0) is the current market (book) value of the firm, Y_t is total earnings in year t, dB_t is the change in book equity in year t, and r is the stock's long-term average expected return. In words, this equation states that, all else equal, the firm's book-to-market ($\frac{B_0}{M_0}$) and its expected profitability ($\frac{E_0(Y_t)}{B_0}$) are positively related to its expected return while the firm's expected investment ($\frac{E_0(dB_t)}{B_0}$) is negatively related to its expected return. Thus, book-to-market, expected profitability, and expected investment are indicators for expected returns. Fama and French (2015) motivate their value, profitability, and investment factors based on this insight. To proxy for expected profitability and investment, they use current operating profitability and asset growth.

Yet, the variation in book-to-market, profitability, or investment across firms does not only reflect differences in expected returns; that is, only part of the characteristics' variation is informative about expected returns, meaning they are imperfect indicators for expected returns. To formalize this idea, consider the following expression for a given characteristic C's cross-sectional correlation with expected returns:

$$\begin{aligned}\rho_{C,r} &= \frac{cov(C,r)}{\sigma_C \sigma_r} = \frac{cov(C^* + \epsilon_C, r)}{\sigma_C \sigma_r} = \frac{cov(C^*, r) + \overbrace{cov(\epsilon_C, r)}^{=0}}{\sigma_C \sigma_r} \\ &= \frac{cov(C^*, r)\sigma_{C^*}}{\sigma_C \sigma_r \sigma_{C^*}} = \underbrace{\rho_{C^*,r}}_{>\rho_{C,r}} \underbrace{\frac{\sigma_{C^*}}{\sigma_C}}_{<1}\end{aligned} \tag{2}$$

where $C \in \{$book-to-market, profitability, and investment$\}$, C^* denotes the characteristic's part that is informative about expected returns, ϵ_C denotes the characteristic's part that is not informative about expected returns, r denotes expected returns, σ_X denotes the cross-sectional volatility of variable X, $cov(X,Y)$ denotes the cross-sectional covariance between variables X and Y, and $\rho_{X,Y}$ denotes the cross-sectional correlation between variables X and Y. Since the correlation of C^* with expected returns is higher than for C, it is a better indicator for expected returns than the raw characteristic. Our central thesis in this study is that value, profitability, and investment factors that are based on adjusted characteristics rather than the raw characteristics possess better pricing power for the cross-section of stock returns than the standard factors because they reflect more priced covariation.

To narrow down the variation in the characteristics that is informative about expected returns, we aim to cancel their variation that is not informative about expected returns. To this end, we need to have some theoretical intuition why the characteristics reflect differences in expected returns and which other effects drive their variation. First, consider book-to-market. Intuitively, book-to-market is positively related to expected returns because high expected returns imply, in the framework of the dividend discount model, that investors apply high discount rates to future dividends. High discount rates therefore lead to lower stock prices and, in turn, to depressed market values relative to book values. Thus, the variation in book-to-market that is informative about expected returns is related to the variation in market equity rather than book equity. However, in the framework of the dividend discount model, changes in stock prices, and thus in market values, may not only emanate from changes in discount rates (i.e., discount rate shocks) but also from changes in dividend expectations (i.e., cash flow shocks). Since discount rates are in equilibrium equal to expected returns, only the variation in market values due to discount rate shocks is informative about expected returns. By contrast, the variation in market values due to cash flow shocks is not informative about expected returns.

Next, consider investment. In the framework of the net present value rule of investment, firms may invest a lot if the expected cash flows of their potential projects are high or if the cost of capital for realizing the projects are low, or both. Since low cost of capital imply in equilibrium low expected returns, the variation in investment due to differences in cost of capital is informative about expected returns. By contrast, changes in investment due to changes in the projects' expected cash flows (i.e., cash flow shocks) are not informative about expected returns.

Finally, consider profitability. A firm may be highly profitable because the firm realized projects that were ex-ante expected to be very profitable or because the cash flows from the firm's project ex-post turned out to be higher than expected (i.e., the firm experienced positive cash flow shocks). Based on the net present value rule of investment, a firm that realizes only projects that are expected to be highly profitable is likely to have high cost of capital as it would otherwise also realize less profitable projects. Since high cost of capital imply in equilibrium high expected returns, profitability that is high due to high ex-ante expected profitability should be informative about expected returns. Yet, profitability that is high due to positive cash flow shocks may in part also be informative about expected returns. Specifically, positive cash flow shocks imply higher expected cash flows from potential projects, leading to positive net present values for projects with high cost of capital that would otherwise have negative net present values. If the firm realizes these projects, its expected return increases due to the projects' high cost of capital. Consequently, profitability that is high due to such cash flow shocks also is informative about expected returns. By contrast, if profitability is high because of positive cash flow shocks that lead the firm to invest in projects with average cost of capital should not be informative about expected returns.

3 Data and Methodology

3.1 Data Sample

Our sample period spans the time from July 1963 to December 2019. We obtain stock data from CRSP and firm fundamentals data from Compustat. We supplement the Compustat fundamentals data with Davis et al.'s (2000) hand-collected book equity data from Kenneth French's website.[3] Our sample includes all stocks that are traded on the NYSE, AMEX, or NASDAQ and that have a CRSP share code of 10 or 11. We adjust monthly holding period returns for potential delisting returns. Following Shumway (1997) and Shumway and Warther (1999), we additionally set missing delisting returns for NYSE and AMEX stocks to -30% and for NASDAQ stocks to -55% in case the delisting was performance-related. Finally, we use the one-month T-bill rate retrieved from Kenneth French's website as a proxy for the risk-free rate. The construction of our key variables—book-to-market, operating profitability, and investment—is described in detail in Appendix A. It closely follows the variable definitions of Fama and French (2015).

3.2 A Proxy for Cash Flow Shocks

The discussion in Section 2 outlines that variation in book-to-market, profitability, and investment stemming from cash flow shocks is not informative about expected returns. To narrow down the characteristics' variation that is informative about expected returns, we aim to cancel their variation stemming from cash flow shocks. For this purpose, we need a proxy for firms' cash flow shocks. We follow Hou and van Dijk (2019) and use firms' estimated profitability shocks as proxy for their cash flow shocks. In a first step, we implement Hou and van Dijk's (2019) cross-sectional profitability model that yields estimates for firms' expected profitability. Specifically, we run the following cross-sectional regression at the end of each June from 1964 to 2019:[4]

$$\frac{OI_{i,t}}{AT_{i,t-1}} = b_{0,t} + b_{1,t}\frac{FV_{i,t-1}}{AT_{i,t-1}} + b_{2,t}DD_{i,t-1} + b_{3,t}\frac{D_{i,t-1}}{BE_{i,t-1}} + b_{4,t}\frac{OI_{i,t-1}}{AT_{i,t-2}} + \epsilon_{i,t} \tag{3}$$

where $\frac{OI_{i,t}}{AT_{i,t-1}}$ is firm i's operating income after depreciation scaled by lagged total assets, $\frac{FV_{i,t-1}}{AT_{i,t-1}}$ is the ratio of market value to book value of assets (market value of assets is calculated as book value of assets plus market equity (from Compustat) minus book equity (calculated as described in Appendix A)), $\frac{D_{i,t-1}}{BE_{i,t-1}}$ is the ratio of dividend payments to book equity, and $DD_{i,t}$ is a dummy variable that equals one if the firm does not pay dividends; t-variables are measured at the end

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[4] Following Hou and van Dijk (2019), we exclude firms with total assets of less than $10 million and book equity of less than $5 million for the estimation of the model.

of June of year t based on the firm's last fiscal year ending in year $t-1$.

Table 1 presents the average coefficients from the annual regressions. Their signs are identical and their magnitudes are similar to those reported by Hou and van Dijk (2019). In line with intuition, the coefficients indicate that expected profitability is higher for firms with higher valuations, higher dividend payments, and higher past profitability.

[Insert Table 1 near here.]

Like Hou and van Dijk (2019), we use the annual regression coefficients from the profitability model in (3) to calculate firms' profitability shocks. In particular, we forecast firm i's profitability for year t by multiplying the estimated coefficients from the regression in year $t-1$ with the firm's values for the predictor variables in year $t-1$. The firm's profitability shock in year t, $PS_{i,t}$, is then its realized profitability in year t minus its forecasted profitability; that is:

$$PS_{i,t} = \frac{OI_{i,t}}{AT_{i,t-1}} - E_{t-1}\left(\frac{OI_{i,t}}{AT_{i,t-1}}\right) = \frac{OI_{i,t}}{AT_{i,t-1}} - X_{i,t-1}\hat{b}'_{t-1} \tag{4}$$

where $X_{i,t-1}$ is a vector that contains firm i's values for the predictors as of year $t-1$ and $\hat{b}_{t-1}$ is the vector of coefficients estimated from regression (3) in year $t-1$. $PS_{i,t}$ is our proxy for firm i's cash flow shock across the fiscal year that ended in year $t-1$.

3.3 Identification of Book-to-Market's Pricing Information

The discussion in Section 2 outlines that we need to identify book-to-market's variation due to market equity changes, and that we then need to cancel the variation due to cash flow shocks from book-to-market's market equity-driven part to narrow down book-to-market's predictive information. To identify book-to-market's variation due to market equity changes, we follow Gerakos and Linnainmaa (2018) and regress book-to-market on lagged market equity changes. Specifically, we run the following cross-sectional regression at the end of each June from 1968 to 2019:

$$BM_{i,t} = b_{0,t} + \underbrace{\sum_{l=1}^{5} b_{l,t} dME_{i,t-l+1}}_{BM_{i,t}^{me}} + \epsilon_{i,t} \tag{5}$$

where $BM_{i,t}$ is firm i's log book-to-market and $dME_{i,t}$ is the log change in the firm's market equity. t-variables are measured at the end of June of year t based on the firm's last fiscal year ending in year $t-1$. We estimate the regressions using weighted least squares with firms' market capitalizations as weights. Moreover, we winsorize all variables at the 0.5% and 99.5% levels.

Panel A of Table 2 presents the average coefficients from the annual regressions. The coefficients on all lagged market equity changes are significantly negative. The market equity changes across the past five years explain nearly half of the cross-sectional variation in book-to-market as indicated by the average adjusted R^2 of 48.4%.

[Insert Table 2 near here.]

Having identified book-to-market's market equity-driven part, we cancel the variation due to cash flow shocks. For this purpose, we orthogonalize book-to-market's market equity-driven part to our estimated profitability shocks. Specifically, we run the following cross-sectional regression at the end of each June from 1968 to 2019:

$$\widehat{BM}^{me}_{i,t} = b_{0,t} + \sum_{l=1}^{5} b_{l,t} PS_{i,t-l+1} + \underbrace{\epsilon_{i,t}}_{BM^*_{i,t}} \tag{6}$$

where $\widehat{BM}^{me}_{i,t}$ is the market-equity driven part of firm i's book-to-market as estimated from regression (5), $PS_{i,t}$ is the firm's profitability shock as defined in equation (4), and $BM^*_{i,t}$ is our adjusted book-to-market ratio aiming to be a better indicator for expected returns than the raw book-to-market ratio. t-variables are measured at the end of June of year t based on the firm's last fiscal year ending in year $t-1$. We estimate the regressions using weighted least squares with firms' market capitalizations as weights. Moreover, we winsorize all variables at the 0.5% and 99.5% levels.

Panel B of Table 2 presents the average coefficients from the annual regressions. The coefficients on all lagged profitability shocks are significantly negative. In line with intuition, this result suggests that cash flow shocks negatively affect firm valuations. The profitability shocks across the past five years explain a substantial fraction of the cross-sectional variation of book-to-market's market-equity driven part as indicated by the average adjusted R^2 of 38.6%.

3.4 Identification of Investment's Pricing Information

In Section 2, we argue that canceling the variation in investment due to cash flow shocks should yield a better indicator for expected returns. Therefore, we orthogonalize investment to our estimated profitability shocks. Specifically, we run the following cross-sectional regression at the end of each June from 1968 to 2019:

$$INV_{i,t} = b_{0,t} + \sum_{l=1}^{5} b_{l,t} PS_{i,t-l+1} + \underbrace{\epsilon_{i,t}}_{INV^*_{i,t}} \tag{7}$$

where $INV_{i,t}$ is firm i's log asset growth, $PS_{i,t}$ is the firm's profitability shock as defined in equation (4), and $INV^*_{i,t}$ is our adjusted investment aiming to be a better indicator for expected returns than raw investment. t-variables are measured at the end of June of year t based on the firm's last fiscal year ending in year $t-1$. We estimate the regressions using weighted least squares with firms' market capitalizations as weights. Moreover, we winsorize all variables at the 0.5% and 99.5% levels.

Panel C of Table 2 presents the average coefficients from the annual regressions. The coefficients on all lagged profitability shocks are significantly positive. Consistent with intuition, this result suggests that firms increase their investment when they experience positive cash flow shocks. The profitability shocks across the past five years explain 20.9% of the cross-sectional variation in investment.

3.5 Identification of Operating Profitability's Pricing Information

Narrowing down the variation in profitability that is informative about expected returns is less straightforward than for book-to-market and investment. In Section 2, we argue that variation in profitability stemming from cash flow shocks that lead firms to invest into projects whose cost of capital are similar to the firms' expected returns are not informative about expected returns. By contrast, variation in profitability stemming from cash flow shocks that lead firms to invest into projects whose cost of capital differ from the firms' expected returns are informative about expected returns. Our estimated profitability shocks are not suited to differentiate between cash flow shocks implying changes in expected returns and those that do not.[5] However, whether a cash flow shock implies changes in expected returns or not should be discernible from the changes in market values and investment. Specifically, while a positive cash flow shock should always be accompanied by increases in market values and investment, the increases should be lower for a positive cash flow shock triggering investment into projects with higher cost of capital and thus an increase in expected returns. This is because projects with higher cost of capital exhibit, all else being equal, lower net present values, implying less appreciation in market values and a lower propensity to investment. The same reasoning analogously applies to negative cash flow shocks and decreases in market values and investment.

Given these arguments, we aim to identify the part of our estimated profitability shocks that can be explained by changes in market values and investment.[6] Specifically, we run the following cross-sectional regression at the end of each June from 1964 to 2019:

$$PS_{i,t} = b_{0,t} + \underbrace{b_{1,t} dINV_{i,t} + b_{2,t} dME_{i,t}}_{PS-Fit_{i,t}} + \epsilon_{i,t} \tag{8}$$

where $PS_{i,t}$ is firm i's profitability shock as defined in equation (4), $dINV_{i,t}$ is the change in the firm's log asset growth, and $dME_{i,t}$ is the log change in the firm's market equity. t-variables are

[5] Note that this is not a problem with regard to narrowing down book-to-market's and investment's pricing information because the information about expected returns inherent in cash flow shocks is reflected in these characteristics with the wrong sign and is therefore not discernible anyways.

[6] This approach may be interpreted as an instrumental variables approach that uses the changes in market values and investment as instruments for the part of the estimated profitability shocks that does not capture information about expected returns.

measured at the end of June of year t based on the firm's last fiscal year ending in year $t-1$. We estimate the regressions using weighted least squares with firms' market capitalizations as weights. Moreover, we winsorize all variables at the 0.5% and 99.5% levels.

Panel D of Table 2 presents the average coefficients from the annual regressions. The coefficients on the changes in investment and market equity are positive and highly significant. That is, profitability shocks are, as expected, positively associated with increases in investment and market values.

We use the fitted values from the regression in (8) as proxy for the part of firms' cash flow shocks that does not imply changes in the firms' expected returns. To cancel the variation in profitability stemming from such cash flow shocks, we orthogonalize profitability to the fitted values. Specifically, we run the following cross-sectional regression at the end of each June from 1968 to 2019:

$$OP_{i,t} = b_{0,t} + \sum_{l=1}^{5} b_{l,t} PS-Fit_{i,t-l+1} + \underbrace{\epsilon_{i,t}}_{OP^*_{i,t}} \tag{9}$$

where $OP_{i,t}$ is firm i's operating profitability, $PS-Fit_{i,t}$ is the firm's fitted profitability shock obtained from the regression in (8), and $OP^*_{i,t}$ is our adjusted operating profitability aiming to be a better indicator for expected returns than raw operating profitability. t-variables are measured at the end of June of year t based on the firm's last fiscal year ending in year $t-1$. We estimate the regressions using weighted least squares with firms' market capitalizations as weights. Moreover, we winsorize all variables at the 0.5% and 99.5% levels.

Panel D of Table 2 presents the average coefficients from the annual regressions. The coefficients on all lagged fitted profitability shocks are significantly positive. The fitted profitability shocks across the past five years explain a substantial fraction of the cross-sectional variation in operating profitability as indicated by the average adjusted R^2 of 38.0%..

3.6 Factor Construction

Using our adjusted characteristics, we create new versions of the Fama-French (2015) factors. For this purpose, we precisely follow Fama and French's (2015) methodology to construct the factor portfolios. First, our market factor is the same as the one of Fama and French (2015). Specifically, the market portfolio includes all stocks that are listed on the NYSE, AMEX, or NASDAQ, have a CRSP share code of 10 or 11, and have good market equity data at the beginning of the month. The market portfolio is newly formed at the beginning of each month. The return on our market factor (MP^*) is the value-weighted return on the market portfolio in excess of the one-month T-bill rate.

For the construction of our enhanced value factor, we sort stocks at the end of each June into two groups according to their size at the end of June and into three groups according to their adjusted book-to-market obtained from the regression model in (6). The breakpoints of the sorts are the median market equity and the 30th and 70th percentiles of the adjusted book-to-market ratio of all NYSE stocks. Taking the intersections of the two size groups and the three book-to-market groups yields six portfolios. The return on our enhanced value factor (HML*) is the average of the value-weighted returns on the two high book-to-market portfolios minus the average of the value-weighted returns on the two low book-to-market portfolios.

The profitability and investment factors are constructed in the same way as the value factor, only that the second sort is with respect to our adjusted operating profitability obtained from the regression model in (9), respectively, with respect to our adjusted investment obtained from the regression model in (7). The return on our enhanced profitability factor (RMW*) is the average of the value-weighted returns on the two high operating profitability portfolios minus the average of the value-weighted returns on the two low operating profitability portfolios. The return on our enhanced investment factor (CMA*) is the average of the value-weighted returns on the two low investment portfolios minus the average of the value-weighted returns on the two high investment portfolios. Finally, the return on our enhanced size factor (SMB*) is the average of the returns on the nine small portfolios resulting from the three bivariate sorts minus the average of the returns on the nine big portfolios.

For comparison, we also reconstruct the standard Fama-French (2015) factors, that is, the factors based on the raw book-to-market, operating profitability, and investment characteristics.

4 Enhanced versus Standard Factors

4.1 Summary Statistics

Panel A of Table 3 presents summary statistics on our reconstructed Fama-French (2015) factors. All factors except the size factor have significant monthly mean returns across our sample period from July 1968 to December 2019. They range between 0.53% for the market factor and 0.15% for the size factor. The investment factor exhibits the highest Sharpe ratio (0.14) while the size factor exhibits the lowest Sharpe ratio (0.05).

[Insert Table 3 near here.]

Panel B presents summary statistics on our enhanced factors and compares them to their standard counterparts. All enhanced factors, even the enhanced size factor, have significant monthly mean returns, ranging between 0.53% for the market factor and 0.26% for the size factor. The mean returns of our enhanced factors are unanimously higher than those of their standard counterparts, but the increases are, except for the size factor, not statistically significant. Moreover, all of the enhanced factors' volatilities are lower than those of their standard counterparts.

The higher mean returns and lower volatilities combine to substantial increases of, on average, 50% in the enhanced factors' Sharpe ratios relative to those of their standard counterparts. These Sharpe ratio increases are, except for the value factor, statistically significant. The enhanced factors' higher Sharpe ratios suggest that they exhibit a higher pricing power than the standard Fama-French (2015) factors. Interestingly, the increases in the Sharpe ratios are, in general, less due to the enhanced factors' higher mean returns than their lower volatilities. Thus, our adjusted characteristics do not only reflect larger spreads in expected returns but also identify differences in expected returns with higher certainty than the raw characteristics. Among the enhanced factors, the investment factor again exhibits the highest Sharpe ratio (0.20) while the size factor again exhibits the lowest Sharpe ratio (0.09).

The enhanced size factor exhibits a particularly strong improvement relative to its standard counterpart. This result is somewhat surprising as we do not explicitly aim to improve this factor, being rather a by-product. It implies that controlling for the adjusted characteristics rather than the raw characteristics—and thus for better indicators for expected returns—in the construction of the size factor is beneficial for isolating the pricing information reflected by firm size respectively the size factor.

Beyond the factors' individual summary statistics, Table 3 also presents correlations between the factors. Comparing the standard and enhanced factors' correlations reveals that the correlations between our enhanced value, profitability, and investment factors are lower than the correlations between the standard value, profitability, and investment factors. This observation means that ourenhanced value, profitability, and investment factors capture more independent covariation than their standard counterparts. However, the enhanced value, profitability, and investment factors' correlations with the market and size factors are, by tendency, somewhat higher than those of their standard counterparts. Taken together, it is unclear whether our enhanced factors also improve regarding potential diversification benefits between the factors.

4.2 Maximum Sharpe Ratios

The overarching purpose of factor models is to use them for the pricing of assets. Barillas and Shanken (2017) show that the pricing performance of two models should be compared based on their maximum attainable Sharpe ratios; that is, the higher a factor model's maximum attainable Sharpe ratio, the better its pricing performance. The results in Table 3 show that the individual Sharpe ratios of our enhanced factors are unanimously, and mostly significantly, higher than those of their standard counterparts. Nevertheless, this finding does not yet imply that the maximum Sharpe ratio of a five-factor model using our enhanced factors is higher than for the standard Fama-French (2015) five-factor model as the correlation structure between our enhanced factors may be less advantageous.

Barillas et al. (2020) propose a test to examine whether the (squared) Sharpe ratios, and thus the pricing performance, of two models are significantly different. Moreover, Fama and

French (2018) suggest to test whether the (squared) Sharpe ratios of two models are significantly different based on a bootstrap simulation approach. This approach splits the sample period of T months into $T/2$ adjacent pairs of months. Each simulation run randomly draws $T/2$ pairs with replacement. From each pair, one month is allocated to an in-sample period and the other month to an out-of-sample period. The in-sample months are used to calculate the factor models' in-sample maximum squared Sharpe ratios and to identify the factors' weights in the in-sample tangency portfolios. These in-sample weights are then used to calculate the models' maximum squared Sharpe ratios in the out-of-sample months. While the in-sample Sharpe ratios are upward biased estimates for the models' true Sharpe ratios, the out-of-sample Sharpe ratios should be unbiased estimates for the true Sharpe ratios.

We implement the test of Barillas et al. (2020) as well as the bootstrap simulation approach of Fama and French (2018) to examine whether the Sharpe ratio of our enhanced five-factor model, and thus its pricing performance, significantly improves upon the standard Fama-French (2015) five-factor model. Panel A of Table 4 presents the results. First, our enhanced five-factor model generates an actual maximum squared Sharpe ratio of 0.160 across our entire sample period. This is much higher than the standard five-factor model's maximum squared Sharpe ratio of 0.093, representing, in terms of simple Sharpe ratios, an increase of more than 30% (from 0.30 to 0.40). Barillas et al.'s (2020) test and Fama and French's (2018) bootstrap simulation approach both indicate that the increase of the enhanced model's Sharpe ratio relative to the standard model's Sharpe ratio is highly significant. Specifically, the test statistic from Barillas et al.'s (2020) test is 2.64, meaning the difference is significant at the 1% level. Moreover, the enhanced model's out-of-sample Sharpe ratio is in 97.5% of 100,000 simulation runs higher than for the standard model, corresponding to a significance level of 2.5%. Although the Sharpe ratios from the full-sample and in-sample simulations are biased estimates for the true Sharpe ratios, the enhanced models' outperformance is in these simulations clearly observable as well, beating the standard model in 99.7% respectively 97.1% of these simulation runs.[7]

[Insert Table 4 near here.]

Panel B of Table 4 presents the weights of the factors in the models' tangency portfolios (i.e., in the portfolios attaining the maximum Sharpe ratios) across our sample period. The weights of the value and profitability factors increase in the enhanced model's tangency portfolio relative to the standard model, meaning their contributions to the pricing performance are higher in the enhanced than the standard model. Notably, the value factor's contribution turns from negative to positive. By contrast, the weights of the market and investment factors decrease in the enhanced model's tangency portfolio relative to the standard model, meaning their contributions to the pricing performance are lower in the enhanced than the standard model. Nevertheless, the ordering of the factors' contributions to the pricing performance is in both models the same. Specifically, the investment factor contributes in both models the most while the value factor contributes the least.

[7] The full-sample simulations randomly draw T months with replacement.

4.3 Pricing Factors

The results in Table 4 show that our enhanced five-factor model exhibits a better pricing performance than the standard five-factor model. Nevertheless, the standard factors may still capture pricing information uncaptured by the enhanced factors. To evaluate to what extent the pricing information captured by the standard and enhanced models is complementary, we regress our enhanced factors on the standard factors, and vice versa.

Table 5 presents the results. Panel A shows that each of our enhanced factors captures incremental pricing information with respect to the standard factors. Specifically, all enhanced factors exhibit significantly positive alphas, ranging between 0.06% and 0.22%, when they are regressed on the standard five-factor model. Thus, the standard factors fail to capture the entire pricing information of any of the enhanced factors.

[Insert Table 5 near here.]

Conversely, Panel B shows that the standard value, profitability, and investment factors do not exhibit significant alphas. Thus, they do not capture significant incremental pricing information with respect to the enhanced factors. Put differently, the enhanced factors capture the pricing information of the standard value, profitability, and investment factors. By contrast, the standard size factor exhibits a significantly negative alpha, meaning it captures pricing information with respect to the enhanced factors. However, given that the alpha is negative, this pricing information goes in the opposite direction of the size effect.

4.4 Spanning Regressions

The results in the previous subsections show that our enhanced model achieves a better pricing performance than the standard model and that the enhanced factors capture the standard factors' pricing information reasonably well. Next, we examine the individual factors' incremental pricing power in the models. Barillas and Shanken (2017) argue that a factor significantly improves the pricing performance of a factor model, and thus has significant incremental pricing power, if its alpha with respect to the other factors is significant. Consequently, we conduct spanning regressions that regress each factor on the factor models' other factors to gauge whether the factors possess significant incremental pricing power.

Panel A of Table 6 presents the results for the standard Fama-French (2015) five-factor model. In line with the finding of Fama and French (2015), the value factor exhibits an insignificant alpha of -0.04%, and its positive mean return is primarily captured by the investment factor. Thus, the value factor does not possess incremental pricing power with respect to the other factors in the standard five-factor model, especially the investment factor, and is therefore redundant. This finding is in line with the value factor's small and negative weight in the standard model's tangency portfolio as displayed in Panel B of Table 4. In particular, the value factor's small weight as well as its insignificant alpha both suggest that the value factor hardly contributes to the standard model's pricing performance. Contrary to the value factor, the remaining four factors of the standard model exhibit significantly positive alphas. Thus, they possess significant incremental pricing power and contribute to the model's pricing performance.

[Insert Table 6 near here.]

Panel B of Table 6 presents the results for our enhanced five-factor model. Like the standard value factor, the enhanced value factor exhibits an insignificant alpha and possess therefore no significant incremental pricing power in our enhanced model. The value factor is again primarily subsumed by the investment factor. Nevertheless, the enhanced value factor's alpha of 0.10% is non-negligible and much higher than the standard value factor's alpha. While our approach to enhance the factors is not successful in disentangling the value and investment factors' pricing information, our enhanced value factor captures, at least, more incremental, albeit still insignificant, pricing information than its standard counterpart. This conjecture is also supported by the considerable increase in the value factor's weight in the enhanced model's tangency portfolio as displayed in Panel B of Table 4 relative to the standard model's tangency portfolio (from -3.0% to 5.8%). Contrary to the value factor, the remaining enhanced factors all exhibit highly significant alphas. Thus, all of them possess significant incremental pricing power and contribute to the enhanced model's pricing performance.

In sum, the findings from this section give rise to several conclusions. First, our enhanced factors substantially improve upon the standard factors on an individual basis. These improvements emanate from higher mean returns as well as lower volatilities. Second, the improvements in the individual factors translate to a strong improvement in our enhanced five-factor model's pricing performance relative to the standard Fama-French (2015) five-factor model. Third, our enhanced factors capture nearly the entire pricing information of the standard factors, but the opposite does not hold. Last, all of the enhanced factors, except the enhanced value factor, capture significant incremental pricing information. Nevertheless, the enhanced value factor's non-negligible tangency portfolio weight and alpha indicate that it captures more incremental pricing information than its standard counterpart, and that it therefore may still contribute to the model's pricing performance.

5 Factor Risk Prices

A central prediction of factor pricing models is that assets' expected returns should be linear functions of their exposures to the factors. For a factor model with K factors, this predicted relation can be formally expressed as follows:

$$E(r^e_{i,t}) = \sum_{k=1}^{K} \beta^k_{i,t} \lambda_k \tag{10}$$

where $E(r_{i,t}^e)$ is asset i's expected return in period t in excess of the risk-free rate, $\beta_{i,t}^k$ is the asset's exposure to factor k in period t, and λ_k is the price of risk for exposure to factor k. If a factor k captures a source of systematic risk for which investors demand compensation, the factor's risk price λ_k should be positive. A well-specified factor model should comprise only factors that capture systematic risks, that is, factors with positive risk prices. Such a factor model produces an upward sloping multivariate security market line.

As discussed in Section 1, many factor models, in particular the Fama-French (2015) five-factor model, do not produce an upward sloping security market line; that is, the factors' risk prices λ_k are not reliably positive or are even negative. As they do not satisfy the prediction that expected returns should be positively related to factor exposures, these models are rejected. Section 4 documents that our enhanced five-factor model exhibits a much higher maximum Sharpe ratio than the standard five-factor model. Thus, our enhanced factors should be much better proxies for the mean-variance efficient portfolio than the standard factors and should therefore capture more systematic risks. Consequently, expected returns may be more strongly related to exposures to our enhanced factors than to exposures to the standard factors, meaning our enhanced five-factor model may perform better in producing an upward sloping multivariate security market line.

To evaluate this conjecture, we estimate the standard and enhanced factors' risk prices. For this purpose, we implement the two-stage procedure proposed by Fama and MacBeth (1973). In the first stage, we estimate at the end of each month from June 1969 to December 2019 stocks' betas with respect to the factors. Specifically, we regress their daily returns in excess of the T-bill rate across the previous 12 months on the standard Fama-French (2015) five-factor model as well as our enhanced five-factor model. We require at least 100 daily observations across the 12-month estimation window to estimate a stock's factor betas.

In the second stage, we regress stocks' compounded returns in excess of the compounded one-month T-bill rate across the 12-month estimation window on their estimated betas; that is, we run at the end of each month from June 1969 to December 2019 the following cross-sectional regression:

$$r_{i,t}^e = \gamma_t^{ZB} + \gamma_t^{MP}\hat{\beta}_{i,t}^{MP} + \gamma_t^{SMB}\hat{\beta}_{i,t}^{SMB} + \gamma_t^{HML}\hat{\beta}_{i,t}^{HML} + \gamma_t^{RMW}\hat{\beta}_{i,t}^{RMW} + \gamma_t^{CMA}\hat{\beta}_{i,t}^{CMA} + \epsilon_{i,t} \quad (11)$$

where $r_{i,t}^e$ is stock i's compounded return from the beginning of month $t-11$ to the end of month t in excess of the compounded one-month T-bill rate, and $\hat{\beta}_{i,t}^{MP}$, $\hat{\beta}_{i,t}^{SMB}$, $\hat{\beta}_{i,t}^{HML}$, $\hat{\beta}_{i,t}^{RMW}$, and $\hat{\beta}_{i,t}^{CMA}$ are the stock's market, size, value, profitability, and investment betas estimated from the beginning of month $t-11$ to the end of month t. The coefficients γ_t^{MP}, γ_t^{SMB}, γ_t^{HML}, γ_t^{RMW}, and γ_t^{CMA} obtained from this regression are estimates for the factors' risk prices for the period from month $t-11$ to t. γ_t^{ZB} is the zero-beta rate.[8] We winsorize stocks' excess returns and betas at the 0.5% and 99.5% levels, and we use weighted least squares with stocks' market capitalizations as weights. The final risk premium estimates are obtained by averaging

[8]The estimated zero-beta rate should be zero for a well-specified factor model.

the monthly γ-estimates across the period from June 1969 to December 2019. For comparison, we estimate the factors' risk prices also in an univariate setting, that is, by using only one of the betas at a time in the estimation of the monthly regressions in (11).

The independent variables in regression (11) (i.e., the betas) are estimated and therefore noisy measures of stocks' true factor exposures. For this reason, the coefficient estimates (i.e., the risk prices) may suffer from an errors-in-variables bias. To account for this potential errors-in-variables bias, we estimate the monthly regressions in (11) not only with our weighted least squares approach but also with the instrumental variables approach of Jegadeesh et al. (2019) that aims to eliminate the errors-in-variables bias. Roughly speaking, this approach estimates two sets of betas in the first stage: the first set is estimated based on daily data from the odd months in the respective estimation window, the second set is estimated based on daily data from the even months. The first set of betas is then used as instruments for the second set of betas when aiming to explain stocks' excess returns across the even months, and vice versa. Appendix B provides a detailed description of our implementation of Jegadeesh et al.'s (2019) instrumental variables approach.

Table 7 presents the estimated risk prices for the Fama-French (2015) and our enhanced factors. t-statistics are based on Newey-West (1987) standard errors with 12 lags. Panel A shows that the market and size factors of the Fama-French (2015) model carry significantly positive risk prices no matter whether they are estimated in a univariate or multivariate setting and no matter whether they are estimated with weighted least squares or the instrumental variables approach. Thus, stocks with high exposures to the market and size factors earn higher average returns than stocks with low exposures. This result is in line with the theoretically predicted positive relation between factor exposures and returns.

[Insert Table 7 near here.]

However, the positive relation does not hold for the value, profitability, and investment factors of the Fama-French (2015) model. Specifically, these factors' estimated risk prices are negative no matter whether in a univariate or multivariate setting and no matter the estimation method. The estimates for the value factor's risk price are even unanimously significantly negative. Contrary to the predicted positive relation, higher exposures to the standard value, profitability, and investment factors are thus associated with lower average returns. Moreover, the estimated zero-beta rate is significantly positive for both estimation methods. These two findings—the non-positive risk prices for the value, profitability, and investment factors as well as the non-zero zero-beta rate—indicate that the Fama-French (2015) model is misspecified.

Panel B of Table 7 presents the results for our enhanced five-factor model. As for the Fama-French (2015) model in Panel A, the market and size factors carry significantly positive risk prices no matter whether in a univariate or multivariate setting and no matter the estimation method. These results confirm the predicted positive relation between market and size factor exposures and expected returns for our enhanced five-factor model.

However, the results for our enhanced value, profitability, and investment factors differ from those for their standard counterparts. Specifically, the estimated risk prices for our enhanced profitability and investment factors are almost always positive, in part even significantly, whereas they have been unanimously negative for the standard profitability and investment factors. The estimates for the value factor's risk price, while still mostly negative, are insignificantly different form zero, whereas they have been strongly and significantly negative for the standard value factor. Moreover, the estimates for the zero-beta rate are also statistically indistinguishable form zero for both estimation methods, whereas they have been significantly positive for the standard five-factor model. Amid these findings, our enhanced five-factor model adheres in all of these aspects much more to the theoretical requirements for a well-specified factor model than the standard five-factor model.

The most relevant specification is arguably the multivariate setting estimated with the instrumental variables approach. This is because it accounts for stocks' exposures to all factors simultaneously as well as for the potential errors-in-variables bias. This specification also delivers the most promising results: the estimated risk prices of all factors, except the value factor, are significantly positive, and the zero-beta rate is small and insignificant. Although our enhanced five-factor model is still rejected given the enhanced value factor's non-positive risk price, it generates a reasonable upward sloping multivariate security market line. Our enhanced five-factor model thus improves upon the standard five-factor model in this regard given that the latter fails to produce anything close to an upward sloping multivariate security market line in any specification (see Panel A).

To assess whether the improvements of our enhanced model relative to the standard model are significant, Panel C of Table 7 presents the differences between the enhanced factors' estimated risk prices from Panel B and the standard factors' estimated risk prices from Panel A. The estimates for the market factor's risk price are higher for the enhanced than the standard model, but the differences are not statistically significant. The size factor's univariate risk price estimates are higher for the enhanced than the standard model, but the opposite holds for the multivariate risk price estimates. The differences are again not statistically significant. Thus, the market and size factors' risk prices do not differ substantially between the enhanced and the standard model. This finding is expected given that the market factor is in both models the same and the two models' size factors are highly correlated (see Table 3).

By contrast, the differences between the enhanced value, profitability, and investment factors' risk prices and those of their standard counterparts are unanimously positive and mostly statistically significant. This result holds especially in the multivariate setting. Hence, the improvements of our enhanced model in producing an upward sloping multivariate security market line relative to the standard model are largely significant. Additionally, even though the decrease is not significant, the estimated zero-beta rates are considerably lower for the enhanced than the standard model.

Overall, the results from this section show that our enhanced five-factor model comes much closer to generating a clearly upward sloping multivariate security market line than the standard Fama-French (2015) five-factor model. Besides significantly positive risk prices for the market and size factors, our enhanced model produces, contrary to the standard model, significantly positive risk prices for the profitability and investment factors as well as an insignificant zero-beta rate. Only the non-positive risk price for the value factor indicates that the enhanced model also is misspecified.

6 Comparison to other Improvement Procedures

Our results so far show that our enhanced five-factor model strongly improves upon the standard Fama-French (2015) five-factor model. In recent years, the literature put forward several other procedures aiming to improve the standard Fama-French (2015) five-factor model. In this section, we evaluate how our improvement procedure compares to these alternative improvement procedures and whether it complements or substitutes them.

6.1 Hedged Factors

The first alternative improvement procedure we consider is the hedging of factors as proposed by Daniel et al. (2020). The goal of this procedure is to hedge the factors' unpriced sources of variation to reduce their volatility without affecting their mean returns. The approach is to construct so-called hedge portfolios for the factors that have high exposures to the factors but close to zero mean returns. The factors' unpriced variation is then, roughly speaking, hedged by going long the factors' standard versions and short their hedge portfolios. Appendix C provides details on the exact procedure to construct the hedged versions for the factors of a given factor model. It follows closely the procedure proposed by Daniel et al. (2020).

Panel A of Table 8 presents results on the hedged versions of the standard Fama-French (2015) factors. The hedged factors' mean returns are slightly lower than the standard factors' mean returns, but the hedged factors' volatilities also decrease relative to the standard factors' volatilities (see Panel A of Table 3). The latter effect dominates the former effect such that the hedged factors' Sharpe ratios are higher than those of the standard factors. This result is in line with the findings of Daniel et al. (2020) and indicates that the hedging improves the standard Fama-French (2015) factors. Like in the Fama-French (2015) model as well as our enhanced model, the value factor is redundant in the hedged model, exhibiting a marginally insignificant alpha with respect to the other factors. The remaining factors exhibit significant alphas and thus capture significant incremental pricing information.

[Insert Table 8 near here.]

The last five columns of Panel A compare our enhanced factors to the hedged factors. Our enhanced factors' mean returns are unanimously higher than those of the hedged factors, in part even significantly. Yet, only the Sharpe ratio of our enhanced profitability factor is significantly higher than the Sharpe ratio of its hedged counterpart. The Sharpe ratios of the remaining enhanced factors are quite similar to those of their hedged counterparts.

The last two columns display alphas from regressing the hedged factors on our enhanced five-factor model, and vice versa. Our enhanced model produces significant alphas for the hedged market, value, and investment factors, meaning it cannot price these factors. Conversely, the hedged model cannot price our enhanced value, profitability, and investment factors. These results imply that our enhanced factors capture pricing information uncaptured by the hedged factors, and vice versa. Thus, the two sets of factors contain in part complementary pricing information.

Panel C compares the maximum Sharpe ratios, and thus the pricing performance, of the enhanced and hedged models. Across the entire sample period, the enhanced model's maximum squared Sharpe ratio is slightly lower than the hedged model's maximum squared Sharpe ratio (0.160 vs. 0.171). Applying the test of Barillas et al. (2020) yields a test statistic of -0.290. Implementing the bootstrap simulation approach of Fama and French (2018) shows that the enhanced model has in 59.9% of simulation runs a lower out-of-sample maximum Sharpe ratio than the hedged model. Both of these results imply that the maximum Sharpe ratios of the enhanced and hedged models are not significantly different. Thus, the models' pricing power is quite similar.

So far, the results from Table 8 suggest that our enhanced five-factor model competes well with the hedged five-factor model but that both capture complementary pricing information. This raises the question of how a factor model performs that combines both improvement procedures. For this reason, we apply the hedging procedure to our enhanced factors. We refer to the resulting factors as enhanced hedged factors. Panel B of Table 8 presents results on the enhanced hedged factors. The enhanced hedged factors exhibit slightly lower mean returns and considerably lower volatilities than the enhanced factors (see Panel B of Table 3), resulting in unanimously higher Sharpe ratios. Interestingly, all of the enhanced hedged factors exhibit significant alphas in spanning regression. Thus, neither of the enhanced hedged factors is redundant, not even the value factor. These findings suggest that the hedging is, on an individual basis, beneficial for our enhanced factors.

The last five columns of Panel B compare our enhanced hedged factors to the standard hedged factors. Our enhanced hedged factors exhibit uniformly higher mean returns and Sharpe ratios than the standard hedged factors. Although the differences are in parts considerable, they are mostly statistically insignificant. Importantly, our enhanced hedged size, value, profitability, and investment cannot be priced by the hedged five-factor model given their significantly positive alphas. Yet, our enhanced hedged five-factor model also fails to price the hedged factors entirely, producing significantly positive alphas for the hedged value and investment factors. While this result suggests that the hedged model still captures incremental pricing information beyond the enhanced hedged model, the latter seems to capture more independent pricing information.

This conjecture is corroborated by the results in Panel C: the enhanced hedged model exhibits a substantially higher maximum squared Sharpe ratio than the standard hedged model (0.235 vs. 0.171). The test of Barillas et al. (2020) produces a test statistic of 1.799, and the enhanced hedged model achieves in 89.1% of bootstrap simulation runs a higher out-of-sample maximum Sharpe ratio than the standard hedged model. Thus, the difference between the Sharpe ratios is borderline significant at the 10% level. Consequently, the enhanced hedged model exhibits a clearly better pricing performance than the standard hedged model.

Finally, Panel D of Table 8 presents risk price estimates for the standard hedged and the enhanced hedged factors. We estimate the risk prices in a multivariate setting using weighted least squares as well as the instrumental variables approach (the methodology is the same as in Section 5). Amid the results from Panel C that the hedged five-factor model exhibits a similar pricing performance as our enhanced five-factor model, one might expect it also produces a reasonable upward sloping multivariate security market line. This is, however, not the case: only the risk price estimates for the hedged market factor are robustly significantly positive. The risk price estimates for the hedged size factor are positive but far from significant, and the risk price estimate for the hedged investment factor is only significantly positive when the instrumental variables approach is used. The risk price estimates for the hedged value and profitability factors are even negative. The estimates for the zero-beta rate are large and significantly respectively marginally insignificantly positive. These results suggest that the hedged five-factor model adheres much less to the theoretical requirements for a well-specified factor model than our enhanced five-factor model.

The enhanced hedged factors improve somewhat upon the standard hedged factors in producing an upward sloping multivariate security market line. The enhanced hedged value, profitability, and investment factors exhibit higher risk prices, in part significantly, than their standard hedged counterparts. Yet, the market factor's risk price is no longer robustly significantly positive, and the risk price estimates for the size factor decrease. Moreover, the estimates for the zero-beta rate are significantly positive. Thus, the enhanced hedged factors do worse in producing an upward sloping multivariate security market line than our usual enhanced factors (see Panel B of Table 7).

To conclude, the results from this subsection indicate that the enhanced and hedged factor models compete well with each other regarding their pricing performance. Thereby, their pricing information is in part complementary. Combining our procedure to enhance the Fama-French (2015) factors with Daniel et al.'s (2020) procedure to hedge the factors leads to further improvements regarding their mean-variance efficiency. However, the standard hedged as well as the enhanced hedged five-factor model perform considerably worse than our usual enhanced five-factor model in generating an upward sloping multivariate security market line. Both of them thus adhere less to the theoretical requirements for a well-specified factor model.

6.2 Cross-Section Factors

The second alternative improvement procedure we consider is the construction of factors from cross-sectional Fama-MacBeth (1973) regressions as proposed by Fama and French (2020). The factors are obtained as the regression slopes from Fama-MacBeth (1973) regressions that regress the returns of the factor portfolios of a given factor model on the characteristics based on which the factor portfolios are constructed (i.e., market equity, book-to-market, operating profitability, and investment in case of the Fama-French (2015) factors). These regression slopes can be interpreted as zero-investment portfolios that have only exposure to the respective characteristic but zero exposure to the other characteristics. Given that these factors are obtained from a regression, and thus an optimization, they can be expected to improve upon the standard factors based on ad hoc portfolio sorts. Appendix D provides details on the exact procedure to construct the cross-section versions for the factors of a given factor model. It follows closely the procedure proposed by Fama and French (2020).

Panel A of Table 9 presents results on the cross-section versions of the Fama-French (2015) factors. The mean returns of the cross-section factors, apart from the size factor, are significantly positive, and their Sharpe ratios are, in general, somewhat higher than those of the standard Fama-French (2015) factors (see Table 3). This result indicates that the cross-section versions of the factors in fact improve upon the standard versions. Noteworthy, the cross-section size and value factors are redundant in the cross-section five-factor model, exhibiting statistically insignificant alphas with respect to the other factors. By contrast, the cross-section profitability and investment factors have significantly positive alphas and thus possess significant incremental pricing power.

[Insert Table 9 near here.]

The last five columns of Panel A compare our enhanced factors to the cross-section factors. Our enhanced factors have higher Sharpe ratios than the corresponding cross-section factors, but the Sharpe ratio difference is only for the size factor significant. Moreover, our enhanced five-factor model performs quite well in pricing the cross-section factors, producing only for the investment factor a significantly positive alpha. By contrast, the cross-section five-factor model performs badly in pricing our enhanced factors, leaving significantly positive alphas for the enhanced value, profitability, and investment factors. Thus, our enhanced factors capture the pricing information of the cross-section factors much better than vice versa. Nevertheless, the two sets of factors still contain some complementary pricing information.

Panel C of Table 9 compares the enhanced and the cross-section models' pricing performance based on their maximum Sharpe ratios. The enhanced model's maximum squared Sharpe ratio is considerably higher than the cross-section model's Sharpe ratio (0.160 vs. 0.113). Applying the test of Barillas et al. (2020) yields a test statistic of 1.762. The bootstrap approach shows that our enhanced model has in 89.7% of the simulation runs a higher out-of-sample maximum Sharpe ratio than the cross-section model. Based on these two tests, we conclude that the Sharpe ratio difference between the enhanced and the cross-section model is borderline significant at the 10% level; that is, the enhanced model achieves a significantly better pricing performance than the cross-section model.

So far, the results in Table 9 indicate that the cross-section factors perform worse than our enhanced factors. Yet, the cross-section factors seem to perform better than their standard counterparts. To investigate whether combining the cross-section procedure with our improvement procedure, we construct cross-section versions of our enhanced factors following the methodology described in Appendix D. We refer to the resulting factors as enhanced cross-section factors. Panel B of Table 9 presents results on the enhanced cross-section factors. Contrary to the standard cross-section factors, all of the enhanced cross-section factors exhibit significantly positive mean returns and spanning regression alphas. Thus, all of the enhanced cross-section factors capture significant incremental pricing information. However, the enhanced cross-section factors exhibit, in general, lower Sharpe ratios than our usual enhanced factors (see Table 3), indicating that the cross-section procedure is much less beneficial for our enhanced factors than the standard Fama-French (2015) factors.

The last five columns of Panel B compare the enhanced cross-section factors to the cross-section factors. Only the enhanced cross-section size factor exhibits a higher mean return than its standard cross-section counterpart. By contrast, the mean returns of the enhanced cross-section value, profitability, and investment factors are lower than those of their cross-section counterparts, albeit the difference is only for the investment factor significant. The picture improves somewhat regarding the Sharpe ratios: the size factor's Sharpe ratio increases significantly, the value and profitability factors' Sharpe ratios are similar, and the investment factor's Sharpe ratio decreases significantly for the enhanced cross-section factors compared to their cross-section counterparts. Nevertheless, these results indicate that the enhanced cross-section factors hardly improve upon their cross-section counterparts.

When regressing the enhanced cross-section factors on the standard cross-section five-factor model, the enhanced cross-section size and profitability factors exhibit significant alphas. Thus, they cannot be priced by the standard cross-section factors. By contrast, the enhanced cross-section value and investment factors can be priced by the standard cross-section model. Conversely, the enhanced cross-section five-factor model can price the standard cross-section size, value, and profitability factors. Yet, it fails to price the standard cross-section investment factor, leaving a significantly positive alpha. On balance, both sets of factors therefore seem to capture incremental pricing information with respect to each other.

The results so far suggest that the enhanced cross-section factors individually hardly improve upon the standard cross-section factors. Nevertheless, Panel C of Table 9 documents that the enhanced cross-section five-factor model exhibits a higher maximum Sharpe ratio than the standard cross-section five-factor model (0.138 vs. 0.113). The test of Barillas et al. (2020) produces a test statistic of 1.038, and the enhanced cross-section model exhibits in 76.9% of bootstrap simulation runs a higher out-of-sample maximum Sharpe ratio than the standard cross-section model. While these results imply that the enhanced cross-section model achieves a better pricing performance than the standard cross-section model, the improvement in the pricing performance is not statistically significant. Furthermore, the enhanced cross-section model's Sharpe ratio of 0.138 represents a decline compared to the enhanced model's Sharpe ratio of 0.160. Overall, combining the cross-section improvement procedure with our improvement procedure improves the pricing performance relative to the cross-section model but hurts the pricing performance relative to our usual enhanced model.

Finally, Panel D of Table 9 presents risk price estimates for the standard cross-section and the enhanced cross-section factors. The risk prices are again estimated in a multivariate setting. Regarding the standard cross-section model, the market and size factors exhibit significantly positive risk price estimates no matter the estimation method. By contrast, the risk price estimates for the standard cross-section value, profitability, and investment factors are negative, in part even significantly negative. Additionally, the estimates for the zero-beta rate of the standard cross-section model is significantly positive. Thus, the standard cross-section model fails to produce an upward sloping multivariate security market line, meaning it is misspecified.

The enhanced cross-section model improves upon the standard cross-section model in producing an upward sloping multivariate security market line. Specifically, the market and size factors' risk price estimates are again significantly positive. Moreover, the profitability and investment factors exhibit also positive risk price estimates, which are even significantly positive when using the instrumental variables approach. The increases in the profitability and investment factors' risk price estimates relative to their standard cross-section counterparts are significant. Additionally, the estimates for the enhanced cross-section model's zero-beta rate are insignificant. However, the enhanced cross-section model is still rejected given that the risk price estimates for its value factor are negative. The results for the enhanced cross-section factors' risk prices are qualitatively similar to those for the enhanced factors' risk prices in Table 7. Thus, applying the cross-section procedure to our enhanced factors hardly affects our enhanced factors' ability to generate an upward sloping multivariate security market line.

Overall, the findings from this subsection indicate that our improvement procedure strongly outperforms the cross-section procedure in improving the Fama-French (2015) factors. Moreover, while the cross-section procedure improves the Fama-French (2015) factors, it does not improve our enhanced factors. Combining the two procedures deteriorates our enhanced factors on an individual basis and also worsens our enhanced model's pricing performance. To conclude, the cross-section procedure performs clearly worse than our improvement procedure and combining the two procedures do not complement each other.

6.3 Time-Series Efficient Factors

The third alternative improvement procedure we consider is the construction of time-series efficient versions of the factors as proposed by Ehsani and Linnainmaa (2021). This approach builds on the finding of, among others, Ehsani and Linnainmaa (2022) that the factors exhibit positive time-series momentum. The time-series efficient versions of the factors condition on this time-series momentum by, roughly speaking, scaling up (down) the investment in the standard factors if their momentum is positive (negative). Appendix E provides details on the exact procedure to construct the time-series efficient versions for the factors of a given factor model. It follows closely the procedure proposed by Ehsani and Linnainmaa (2021).

Panel A of Table 10 presents results on the time-series efficient versions of the Fama-French (2015) factors. Apart from the market factor, the time-series efficient factors have similar mean returns as their standard counterparts (see Table 3), and all of the mean returns are significantly positive. Yet, the time-series efficient factors exhibit considerably lower volatilities such that their Sharpe ratios are, in general, much higher than those of their standard counterparts. Consistent with the conclusion of Ehsani and Linnainmaa (2021), these results suggest that the factors' time-series efficient versions improve upon their standard versions. Furthermore, like in the standard Fama-French (2015) model as well as our enhanced model, all of the factors except the value factor exhibit significantly positive spanning regression alphas, meaning they capture significant incremental pricing information. By contrast, the value factor again exhibits an insignificant alpha and is thus redundant.

[Insert Table 10 near here.]

The last five columns of Panel A compare our enhanced factors to the time-series efficient factors. The time-series efficient factors' mean returns are, except for the market factor, not significantly different from those of our enhanced factors. Similarly, the Sharpe ratios of the time-series efficient factors also are not significantly different from those of our enhanced factors. Moreover, the time-series efficient factors can hardly be priced by our enhanced factors, and vice versa. Specifically, the time-series efficient market, value, profitability, and investment factors exhibit significant alphas with respect to the enhanced factors. Conversely, the enhanced market, profitability, and investment factors exhibit significant alphas with respect to the time-series efficient factors. Thus, the pricing information captured by the two sets of factors is to a substantial degree complementary.

The time-series efficient factors compare well with our enhanced factors on an individual basis. Nevertheless, Panel C shows that the time-series efficient five-factor model exhibits a considerably lower maximum squared Sharpe ratio than the enhanced five-factor model (0.160 vs. 0.110), implying that our enhanced model's pricing performance is better. However, the test of Barillas et al. (2020) yields a test statistic of only 1.429, indicating that the difference between the models' Sharpe ratios is not statistically significant. The results from the bootstrap approach give rise to the same conclusion: the enhanced model's out-of-sample maximum Sharpe ratio is in 85.8% of simulation runs higher than the time-series efficient model's out-of-sample maximum Sharpe ratio, which is considerable but short of significant. Thus, although our enhanced model achieves a better pricing performance than the time-series efficient model, the improvement is not significant.

The factors' time-series efficient versions improve upon their standard counterparts. To examine whether the time-series efficient procedure also improves our enhanced factors, we construct time-series efficient versions of our enhanced factors following the methodology described in Appendix E. We refer to these factors as enhanced time-series efficient factors. Panel B of Table 10 presents results on the enhanced time-series efficient factors. All of our enhanced time-series efficient factors exhibit significantly positive mean returns. Their mean returns are lower than those of the enhanced factors but so are their volatilities (see Table 3). Their Sharpe ratios are, in general, similar to those of the enhanced factors. Thus, the improvements in our enhanced factors from making them time-series efficient are, if anything, only muted. Moreover, like in the enhanced as well as the time-series efficient five-factor model, the value factor exhibits again an insignificant spanning regression alpha and is thus redundant. The remaining enhanced time-series efficient factors exhibit significantly positive alphas and thus capture incremental pricing information.

The last five columns of Panel B compare the enhanced time-series efficient factors to the standard time-series efficient factors. The enhanced time-series efficient factors' mean returns and Sharpe ratios are not significantly different from those of the standard time-series efficient factors. Thus, the enhanced time-series efficient factors hardly improve upon the standard time-series efficient factors on an individual basis. Nevertheless, the two sets of factors contain in part complementary pricing information. Specifically, the enhanced time-series efficient profitability and investment factors cannot be priced by the standard time-series efficient five-factor model. Conversely, the standard time-series efficient value and profitability factors cannot be priced by the enhanced time-series efficient five-factor model.

While the enhanced time-series efficient factors hardly improve upon the standard time-series efficient factors on an individual basis, Panel C shows that the enhanced time-series efficient model exhibits a much better pricing performance than the standard time-series efficient model. Specifically, the former's maximum squared Sharpe ratio of 0.157 across our sample period is higher than the latter's maximum squared Sharpe ratio of 0.110. Barillas et al.'s (2020) test yields a test statistic of 1.659. Moreover, the enhanced time-series efficient model has in 89.2% of bootstrap simulation runs a higher out-of-sample maximum Sharpe ratio than the standard time-series efficient model. These results indicate that the enhanced time-series efficient model's outperformance is borderline significant at the 10% level. Nevertheless, the enhanced time-series efficient model does not improve upon the pricing performance of our usual enhanced model given its lower maximum squared Sharpe ratio (0.157 vs. 0.160). This result corroborates our conjecture that the time-series efficient procedure does not improve our enhanced factors.

Finally, Panel D of Table 10 presents risk price estimates for the standard time-series efficient and enhanced time-series efficient factors, estimated in a multivariate setting. The performance of the standard time-series efficient factors in producing an upward sloping multivariate security market line is underwhelming. The market and size factors' risk prices are only significantly positive when estimated with weighted least squares but insignificant when estimated with the instrumental variables approach. Even worse, the estimates for the standard time-series efficient value, profitability, and investment factors' risk prices are mostly negative, usually even significantly negative. Moreover, the estimates for the zero-beta rate of the standard time-series efficient model are large and highly significant. Consequently, the time-series efficient model is clearly rejected.

The results are better for the enhanced time-series efficient factors. The risk price estimates for the enhanced time-series efficient factors are, irrespective of the estimation method, almost unanimously and mostly significantly higher than those of the standard time-series efficient factors. Nevertheless, the enhanced time-series efficient model still fails to produce a reasonable upward sloping multivariate security market line. In particular, only the estimates for the size factor's risk price are robustly significantly positive whereas the estimates for the other factors' risk prices are not robustly significantly positive and in part even negative. Additionally, the estimates for the zero-beta rate of the enhanced time-series efficient model are significantly positive. Hence, the enhanced time-series efficient model is also clearly rejected. Importantly, it performs considerably worse in generating an upward sloping multivariate security market line than our usual enhanced model (see Table 7).

In sum, the time-series efficient factors improve the standard Fama-French (2015) factors on an individual basis to a similar degree as our enhanced factors. However, combined in a model, our enhanced factors outperform the time-series efficient factors with regard to their pricing performance and in generating an upward sloping multivariate security market line. Moreover, applying the time-series efficient procedure to our enhanced factors does not lead to improvements. Combining our improvement procedure with the time-series efficient procedure rather harms the performance of our enhanced factors.

7 Conclusion

In this study, we propose a procedure to improve the factors of the Fama-French (2015) five-factor model. We argue that the variation in the characteristics underlying the factors—book-to-market, profitability, and investment—is not only due to differences in expected returns but also due to other effects. Cancelling the part of the characteristics' variation unrelated to differences in expected returns should yield better indicators of expected returns. Factors built from adjusted characteristics that cancel this uninformative variation should improve upon the standard Fama-French (2015) factors.

Our findings confirm this conjecture. First of all, our enhanced factors constructed from the adjusted book-to-market, profitability, and investment characteristics exhibit higher individual Sharpe ratios than the standard Fama-French (2015) factors. The higher Sharpe ratios emanate from higher mean returns as well as lower volatilities compared to the standard factors. This finding means that the adjusted characteristics identify stocks with differential expected returns more accurately and more consistently than the standard factors.

The enhanced factors' higher Sharpe ratios translate to a significantly higher maximum Sharpe ratio for our enhanced five-factor model relative to the Fama-French (2015) five-factor model. This result implies that our enhanced model exhibits a better pricing performance. Thereby, our enhanced factors capture almost the entire pricing information of the Fama-French (2015) factors, but the opposite does not hold.

A central theoretical prediction a well-specified factor model should satisfy is that expected returns should be positively related to factor exposures. The Fama-French (2015) model badly fails to meet this requirement, producing negative risk prices for the value, profitability, and investment factors. Our enhanced model substantially improves in this regard. In line with theoretical requirements, it generates positive risk prices not only for the market and size factors but also for the profitability and investment factors. However, the enhanced model is still rejected as it fails to produce a significantly positive risk price for the value factor. Nevertheless, the enhanced comes much closer in meeting the theoretical requirement for a well-specified asset pricing model to generate an upward sloping multivariate security market line than the standard model.

The recent literature proposed several other procedures to improve the Fama-French (2015) factors. We compare our improvement procedure to the hedging procedure of Daniel et al. (2020), the cross-section procedure of Fama and French (2020), and the time-series efficiency procedure of Ehsani and Linnainmaa (2021). Our procedure does better than all of these procedures in improving the individual factors' Sharpe ratios. Furthermore, our enhanced model achieves a better pricing performance than the cross-section and the time-series efficient models; the hedged model is the only model that can compete with our enhanced model in this regard. Importantly, our enhanced model outperforms all of the other models by large margins in generating an upward sloping multivariate security market line. Moreover, we show that combining our improvement procedure with the hedging procedure yields in general further strong improvements; that is, our procedure is complementary to the hedging procedure. By contrast, combining our procedure with the cross-section procedure or the time-series efficient procedure does not lead to further improvements—if anything, applying these two procedures to our enhanced factors harms their performance.

The empirical asset pricing literature put forward many factors and multifactor asset pricing models. Our findings have important implications on how to construct factors and to set up factor models. In particular, most studies are content with identifying an indicator of expected returns—no matter whether theoretically motivated—and to construct a factor based on this indicator. This approach is not sufficient, not even for theoretically motivated factors like the Fama-French (2015) factors, to obtain factors with good pricing performance. Our results rather suggest that the variation in the indicator informative about expected returns should be narrowed down before constructing the factor. We show that factors following this principle have the potential to achieve a much better pricing power and to adhere much more to the requirements for a well-specified factor model. Importantly, improving existing, theoretically motivated factors counteracts the growth of the factor zoo outlined by Cochrane (2011) and keeps the description of stock returns low-dimensional.

Our findings yield also new insights for the implementation of factor investing strategies. Factor investing strategies based on expected return indicators whose variation related to other effects is cancelled can harvest the factor premia more consistently. Moreover, such factor strategies are less correlated with each other, implying increased diversification benefits from combining them in a multifactor context.

A Variable Definitions

Market Equity (ME):

A stock's market equity for the end of month t is calculated as the stock's price at the end of month t times the stock's shares outstanding at the end of month t. To reduce the skewness in ME, we transform it by the natural logarithm. The ME data is considered missing if ME is non-positive.

Book-to-Market Ratio (BM):

A stock's book-to-market ratio for the end of June of year y is calculated as the firm's book equity from the last fiscal year ending in year $y - 1$, divided by the firm's ME at the end of the month of this fiscal year ending.[9] Following Davis et al. (2000), book equity (BE) is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock (depending on availability, the redemption, liquidation, or par value of preferred stock is used, in that order); if the book value of stockholders' equity is not directly available, it is measured as the book value of common equity plus the par value of preferred stock or as the difference between total assets and total liabilities (in that order). To reduce the skewness in BM, we transform it by the natural logarithm. The BM data is considered missing if either ME or BE is non-positive.

Operating Profitability (OP):

A stock's operating profitability for the end of June of year y is calculated as the firm's annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses, divided by the firm's BE, all from the last fiscal year ending in year $y - 1$. The OP data is considered missing if annual revenues data is missing, if data for each of cost of goods sold, interest expense, and selling, general, and administrative expenses is missing, or if BE is non-positive.

Investment (INV):

A stock's investment for the end of June of year y is calculated as the firm's total assets from the last fiscal year ending in year $y-1$ divided by the firm's total assets from the last fiscal year ending in year $y - 2$, minus 1. To reduce the skewness in INV, we transform it by the natural logarithm. The INV data is considered missing if total assets are non-positive.

[9] This construction of BM slightly differs from Fama and French (2015), who divide the book equity by the firm's ME from the end of December of year $y - 1$.

B Instrumental Variables Approach

Our implementation of the instrumental variables approach proposed by Jegadeesh et al. (2019) is as follows: we first split every 12-month estimation window into two subsets on a monthly basis; that is, the first, third, fifth, ... month of the estimation window is assigned to the first subset, and the second, fourth, sixth, ... month of the estimation window is assigned to the second subset. Within each of these two subsets, we estimate stocks' betas with respect to the factors of a given factor model using daily data. Then, we regress each beta estimated based on the first subset on all betas estimated based on the second subset. Formally, we run at the end of each month t from June 1969 to December 2019 the following cross-sectional regression for each beta:

$$\beta_{i,t}^{k,1} = \delta_{0,t}^{2} + \sum_{k=1}^{5} \delta_{k,t}^{2} \cdot \beta_{i,t}^{k,2} + \epsilon_{i,t} \tag{12}$$

where $\beta_{i,t}^{k,1}$ ($\beta_{i,t}^{k,2}$) is stock i's beta with respect to factor k estimated based on the first (second) subset of the estimation window from month $t-11$ to t. We use weighted least squares with stocks' market capitalizations as weights, and we winsorize the betas on the 0.5% and 99.5% levels.

In the second stage, we use the betas' fitted values from (12) as explanatory variables in monthly cross-sectional Fama-MacBeth (1973) regressions like in (11). The dependent variable is the compounded return across the months in the first subset in excess of the compounded one-month T-bill rate. We again use weighted least squares with stocks' market capitalizations as weights, and we winsorize the dependent and independent variables on the 0.5% and 99.5% levels. From these regressions, we obtain monthly estimates for the factors' risk prices.

We repeat the entire procedure by switching the roles of the first and the second subset; that is, the $\beta_{i,t}^{k,1}$ are now the instrumental variables for the $\beta_{i,t}^{k,2}$ in (12), and the dependent variable in the monthly cross-sectional Fama-MacBeth (1973) regressions is the compounded return across the months in the second subset in excess of the compounded one-month T-bill rate. Thereby, we obtain a second set of monthly estimates for the factors' risk prices. We calculate our final estimates for the factors' risk prices by first taking in each month for each factor the average of the two risk price estimates, and then averaging the factors' monthly average risk prices across the entire sample period.

Jegadeesh et al. (2019) highlight that there is the possibility that the cross-product of the dependent betas and the independent betas in the estimation of the regression model in (12) may be close to singular. This would lead to unreasonably large risk price estimates. Following Jegadeesh et al. (2019), we address this issue by treating monthly risk price estimates deviating six or more standard deviations of the corresponding factor from their mean as missing.

C Hedged Factors

We construct hedged versions for the factors of a given factor model following the methodology of Daniel et al. (2020); that is, we construct first hedge portfolios for the factors and then determine the optimal hedge ratios. To construct the hedge portfolios, stocks' betas with respect to the factors of the factor model are estimated from a multivariate regression at the end of June of each year t from 1968 to 2019. As inspired by Frazzini and Pedersen (2014), stocks' factor betas are estimated based on two estimation windows. First, the stocks' as well as the factors' volatilities are calculated from daily log returns across the previous 12 months (i.e., from the beginning of July of year $t-1$ until the end of June of year t). Second, stocks' correlations with the factors as well as the correlations between the factors are calculated from overlapping three-day cumulative log returns across the previous 60 months (i.e., from the beginning of July of year $t-5$ until the end of June of year t). We only consider daily returns for which the respective stock also has non-missing prices for the same and the previous day. Moreover, we do not use the actual factor returns across the previous 12 respectively 60 months but rather hypothetical factor returns. These hypothetical factor returns are obtained by assuming that the factor portfolios on each day across the previous 12 respectively 60 months consisted of the same stocks with the same weighting as the factor portfolios at the end of June of year t (i.e., after the reformation of the factor portfolios). Like Daniel et al. (2020), we include a dummy variable that equals one if the return observation is from the period between between January and June of year t when estimating stocks' factor betas. Finally, we require stocks to have at least 100 daily return observations across the previous 12 months and at least 15 daily return observations across the previous six months.

The stocks' estimated factor betas are used to construct hedge portfolios for the factors at the end of June of year t. To construct the hedge portfolio for the factor model's value factor, stocks are first sorted into terciles according to their market equity at the end of June as well as into terciles according to their book-to-market ratio from the last fiscal year ending in the previous year.[10] Breakpoints are based only on NYSE stocks. Intersecting the size terciles and the book-to-market terciles yields nine portfolios. Within each of these nine portfolios, stocks are sorted into terciles according to their estimated beta on the value factor. The stocks in each of the 27 resulting portfolios are value-weighted. The hedge portfolio for the value factor is obtained by going long the equal-weighted combination of the nine high value beta portfolios and short the equal-weighted combination of the nine low value beta portfolios.

The hedge portfolios for the factor model's profitability (investment) factor is constructed in the same way as the value factor's hedge portfolio, only that the respective measure of operating profitability (investment) and the beta on the profitability (investment) factor are used. For the construction of the hedge portfolios for the factor model's market and size factors, the 27 portfolios from the bivariate sorts on market equity and any of book-to-market, operating

[10]The book-to-market ratio used for the sort is the book-to-market ratio used for the construction of the respective value factor. That is, the book-to-market ratio used to construct the hedge portfolio of our enhanced value factor is the adjusted book-to-market ratio defined in Section 3.3.

profitability, and investment are used. To construct the market factor's hedge portfolio, the stocks within each of the 27 portfolios are sorted into terciles according to their estimated betas on the market factor. The stocks in each of the 81 resulting portfolios are value-weighted. The hedge portfolio for the market factor is obtained by going long the equal-weighted combination of the 27 high market beta portfolios and short the equal-weighted combination of the 27 low market beta portfolios. The hedge portfolio for the size factor is obtained analogously using the estimated betas on the size factor rather than the market factor.

Following Daniel et al. (2020), the factors' hedged versions are constructed by combining their unhdeged versions with the factors' hedge portfolios as follows:

$$r_t^{f,H} = r_t^f - r_t^h \delta_t^f \tag{13}$$

where $r_t^{f,H}$ is the return on factor f's hedged version in month t, r_t^f is the return on factor f's unhedged version in month t, r_t^h is the vector of returns on the factors' hedge portfolios in month t, and δ_t^f is the vector of factor f's hedge ratios in month t. The hedge ratios are the betas of the unhedged factors on the hedge portfolios and are determined at the end of June as well. Like for the estimation of stocks' factor betas, volatilities are calculated from daily log returns across the previous 12 months and correlations are calculated from overlapping three-day cumulative log returns across the previous 60 months. Again, hypothetical factor and hedge portfolio returns obtained by assuming constant portfolio compositions and weightings across the estimation windows are used rather than the actual factor and hedge portfolio returns.

We denote the hedged versions of the Fama-French (2015) market, size, value, profitability, and investment factors as $\mathrm{MP^H}$, $\mathrm{SMB^H}$, $\mathrm{HML^H}$, $\mathrm{RMW^H}$, and $\mathrm{CMA^H}$, and the hedged versions of our enhanced market, size, value, profitability, and investment factors as $\mathrm{MP^{H*}}$, $\mathrm{SMB^{H*}}$, $\mathrm{HML^{H*}}$, $\mathrm{RMW^{H*}}$, and $\mathrm{CMA^{H*}}$.

D Cross-Section Factors

We construct cross-section versions for the factors of a given factor model following the methodology of Fama and French (2020). The construction of the cross-section factors is based on the 18 portfolios used to construct the usual time-series versions of the factors, that is, based on the portfolios resulting from the bivariate sorts on size and any of book-to-market, operating profitability, and investment (respectively their adjusted versions). The cross-section factors are obtained from monthly Fama-MacBeth (1973) regressions that regress the factor portfolios' returns on their characteristics:

$$r_{p,t} = r_{Z,t} + r_{ME,t}ME_{p,t} + r_{BM,t}BM_{p,t} + r_{OP,t}OP_{p,t} + r_{INV,t}INV_{p,t} + \epsilon_{p,t} \tag{14}$$

where $r_{p,t}$ is portfolio p's return in month t, $ME_{p,t}$ is the portfolio's market equity, $BM_{p,t}$ is the portfolio's book-to-market, $OP_{p,t}$ is the portfolio's operating profitability, and $INV_{p,t}$ is the portfolio's investment.

In case of the Fama-French (2015) five-factor model, book-to-market, operating profitability, and investment are the raw versions described in Appendix A; in case of our enhanced five-factor model, book-to-market, operating profitability, and investment are the adjusted versions described in Section 3. The portfolios' characteristics are calculated as the value-weighted averages of their constituent stocks' characteristics. Market equity is from the beginning of month t; book-to-market, operating profitability, and investment are from the last fiscal year ending in the previous year if t is between July and December and from the last fiscal year ending in the year before the previous year if t is between January and June (i.e., the characteristics are the same as those used for the construction of the portfolios). The portfolios' characteristics are standardized to have a mean of zero and a standard deviation of one.

The cross-section versions of the size, value, profitability, and investment factors are the estimated coefficients $r_{ME,t}$, $r_{BM,t}$, $r_{OP,t}$, and $r_{INV,t}$, respectively, from the regression in (14). Since the relation of market equity and investment with returns is negative, we multiply $r_{ME,t}$ and $r_{INV,t}$ by -1 to obtain the usual positive factor mean returns. In addition to the monthly returns on the cross-section factors obtained from the monthly Fama-MacBeth (1973) regressions, we obtain their daily returns by conducting the Fama-MacBeth (1973) regressions on a daily basis.

We denote the cross-section versions of the Fama-French (2015) size, value, profitability, and investment factors as SMB^{CS}, HML^{CS}, RMW^{CS}, and CMA^{CS}, and the cross-section versions of our enhanced size, value, profitability, and investment factors as $\text{SMB}^{\text{CS*}}$, $\text{HML}^{\text{CS*}}$, $\text{RMW}^{\text{CS*}}$, and $\text{CMA}^{\text{CS*}}$. Following Fama and French (2018), we add the standard market factor described in Section 3.6 to both sets of cross-section factors.

E Time-Series Efficient Factors

We construct time-series efficient versions for the factors of a given factor model following the methodology of Ehsani and Linnainmaa (2021). Specifically, we construct the real-time implementable versions of the time-series efficient factors; they are obtained as follows:

$$\begin{aligned} r_t^{f,TE} &= w_t^f r_t^f \\ w_t^f &= \mu_t \frac{SR_t^2 + 1}{SR_t^2 + \rho_t^2} \frac{\mu_t(1-\rho_t) + \rho_t r_{t-1}^f}{(\mu_t(1-\rho_t) + \rho_t r_{t-1}^f)^2 + (1-\rho_t^2)\sigma_t^2} \end{aligned} \tag{15}$$

where $r_t^{f,TE}$ is the return on factor f's time-series efficient version in month t, r_t^f is the return on the factor's standard version in month t, and μ_t, σ_t, SR_t, and ρ_t are estimates for the factor's expected return, standard deviation, Sharpe Ratio, and first-order autocorrelation, respectively, in month t. w_t^f is constrained to be in the interval [0,1].

μ_t, σ_t, SR_t, and ρ_t are newly estimated each month based on data across the past 120 months. Thereby, the parameters for factor f are not estimated based only on data for factor f but rather based on pooled data across all factors of the respective factor model. Consequently, the same parameter estimates are used for all factors of the factor model. Following Ehsani and Linnainmaa (2021), we require at least two months of prior data to estimate the parameters; that is, the time-series efficient factors are first calculated in September 1968. Moreover, daily versions of the time-series efficient factors are constructed by conditioning in (15) on factors' previous day returns rather than their previous month returns.

We denote the time-series efficient versions of the Fama-French (2015) market, size, value, profitability, and investment factors as MP^{TE}, SMB^{TE}, HML^{TE}, RMW^{TE}, and CMA^{TE}, and the time-series efficient versions of our enhanced market, size, value, profitability, and investment factors as $\text{MP}^{\text{TE*}}$, $\text{SMB}^{\text{TE*}}$, $\text{HML}^{\text{TE*}}$, $\text{RMW}^{\text{TE*}}$, and $\text{CMA}^{\text{TE*}}$.

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Table 1
Profitability Shock Estimation

This table displays time-series averages of regression coefficients from the cross-sectional profitability model of Hou and van Dijk (2019). The regressions are estimated at the end of each June from 1964 to 2019 using common US stocks traded on the NYSE, AMEX, or NASDAQ with total assets above $10 million and book equity above $5 million. The dependent variable is operating income-to-total assets as measured at the end of June. The independent variables are market-to-book value of assets (FV/AT), a dummy variable that equals one if the firm does not pay dividends (DD), the dividend-to-book equity ratio (D/BE), and operating income-to-total assets (OI/AT). The independent variables are lagged by one year with respect to the dependent variable. The variables are constructed as described in Appendix A and are measured at the end of June. Multiplying the estimated coefficients from an annual regression with the contemporaneous independent variables yields a prediction for firms' operating income-to-total assets across the next fiscal year. R^2 is the average adjusted R-squared across all annual regressions. t-statistics are reported in parentheses and are based on Newey-West (1987) heteroskedasticity-robust standard errors with five lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Intercept	FV/AT	DD	D/BE	OI/AT	R^2
Coefficient	0.0155***	0.0064**	−0.0128***	0.0675***	0.7187***	0.613
	(7.37)	(2.14)	(−4.50)	(3.65)	(40.55)	

Table 2
Identification of the Pricing Information of the Characteristics

This table displays time-series averages of regression coefficients from cross-sectional Fama-MacBeth (1973) regressions. The regressions are estimated at the end of each June from 1968 (exception Panel D: 1964) to 2019 using all common US stocks traded on the NYSE, AMEX, or NASDAQ. In Panel A (C, E), the dependent variable is book-to-market (investment, operating profitability). In Panel B, the dependent variable is book-to-market's market equity-driven part, which is calculated as the fitted value from the regression in Panel A. In Panel D, the dependent variable is the profitability shock as calculated in Section 3.2. The independent variables are the change in market equity (dME), the change in investment (dINV), the profitability shock (PS), and the fitted profitability shock obtained from the regression in Panel D (PS-Fit). dME is the annual log-change in the market equity used in the calculation of book-to-market. The variables are constructed as described in Appendix A, are measured at the end of June, and are winsorized at the 0.5%- and 99.5%-level. The regressions are estimated with weighted least squares with the stocks' market capitalizations as weights. A subscript $t - l$ indicates that the respective variable is lagged by l years. R^2 is the average adjusted R-squared across all annual regressions. t-statistics are reported in parentheses and are based on Newey-West (1987) heteroskedasticity-robust standard errors with five lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Market Equity-Driven Part of Book-to-Market

	Intercept	dME_t	dME_{t-1}	dME_{t-2}	dME_{t-3}	dME_{t-4}	R^2
Coefficient	−0.69***	−0.62***	−0.44***	−0.36***	−0.26***	−0.19***	0.484
	(−4.64)	(−8.93)	(−6.58)	(−5.66)	(−4.21)	(−3.23)	

Panel B: Orthogonalization of Book-to-Market's Market Equity-Driven Part to Profitability Shocks

	Intercept	PS_t	PS_{t-1}	PS_{t-2}	PS_{t-3}	PS_{t-4}	R^2
Coefficient	−0.14***	−1.38***	−1.07***	−0.94***	−0.96***	−0.55***	0.386
	(−3.23)	(−4.86)	(−5.68)	(−4.88)	(−3.43)	(−2.91)	

Panel C: Orthogonalization of Investment to Profitability Shocks

	Intercept	PS_t	PS_{t-1}	PS_{t-2}	PS_{t-3}	PS_{t-4}	R^2
Coefficient	0.09***	0.92***	0.31***	0.19***	0.17***	0.04*	0.209
	(9.92)	(10.30)	(10.01)	(5.91)	(6.09)	(1.86)	

Panel D: Regression of Profitability Shocks on Changes in Investment and Market Equity

	Intercept	dINV	dME	R^2
Coefficient	0.01*	0.09***	0.04***	0.287
	(1.81)	(6.68)	(10.63)	

Panel E: Orthogonalization of Profitability to Fitted Profitability Shocks

	Intercept	$PS\text{-}Fit_t$	$PS\text{-}Fit_{t-1}$	$PS\text{-}Fit_{t-2}$	$PS\text{-}Fit_{t-3}$	$PS\text{-}Fit_{t-4}$	R^2
Coefficient	0.35***	0.59**	0.69***	0.63**	0.31	0.11	0.380
	(17.19)	(2.35)	(2.88)	(2.32)	(0.99)	(0.58)	

Table 3
Summary Statistics of Factors

Panel A of this table displays monthly mean returns (in percent), volatilities (in percent), and Sharpe ratios for the standard Fama-French (2015) market (MP), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. It also displays the correlations between the factors' monthly returns. Panel B displays the same statistics for the enhanced market (MP*), size (SMB*), value (HML*), profitability (RMW*), and investment (CMA*) factors. Panel B also displays statistics on the comparison between the enhanced and the standard factors: "Diff" shows the difference between the mean returns of the enhanced and the respective standard factors; "Corr" shows the correlation between the monthly returns of the enhanced and the respective standard factors; "dSR" shows the difference between the Sharpe ratios of the enhanced and the respective standard factors. The factors are constructed as described in Section 3.6. The sample period is from July 1968 to December 2019. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fama-French Factors

				Correlations				
	Mean	Std	SR	MP	SMB	HML	RMW	CMA
MP	0.53***	4.49	0.12	1.000	0.256	−0.270	−0.261	−0.389
	(2.93)							
SMB	0.15	2.97	0.05		1.000	−0.095	−0.371	−0.064
	(1.22)							
HML	0.31***	2.81	0.11			1.000	0.151	0.679
	(2.76)							
RMW	0.26***	2.28	0.12				1.000	−0.015
	(2.88)							
CMA	0.25***	1.80	0.14					1.000
	(3.51)							

Panel B: Enhanced Factors

				Correlations					Comparison to Fama-French		
	Mean	Std	SR	MP*	SMB*	HML*	RMW*	CMA*	Diff	Corr	dSR
MP*	0.53***	4.49	0.12	1.000	0.213	−0.168	−0.191	−0.387	0.00	1.000	0.00
	(2.93)										(0.00)
SMB*	0.26**	2.91	0.09		1.000	0.164	−0.384	0.042	0.11***	0.973	0.04***
	(2.21)								(4.10)		(4.01)
HML*	0.33***	2.11	0.16			1.000	−0.065	0.492	0.02	0.662	0.05
	(3.88)								(0.20)		(1.18)
RMW*	0.28***	1.55	0.18				1.000	−0.045	0.02	0.706	0.07*
	(4.50)								(0.25)		(1.86)
CMA*	0.28***	1.40	0.20					1.000	0.02	0.735	0.06*
	(4.88)								(0.42)		(1.93)

Table 4
Models' Maximum Sharpe Ratio

Panel A of this table displays results on the Sharpe ratios of the standard Fama-French (2015) five-factor model and the enhanced five-factor model. "SR^2" is the maximum monthly squared Sharpe ratio across the sample period from July 1968 to December 2019. "BKRS" is the test statistic from testing whether the enhanced model's maximum squared Sharpe ratio is equal to the standard Fama-French (2015) model's maximum squared Sharpe ratio. The remaining columns display mean and median Sharpe ratios from 100,000 full-sample, in-sample, and out-of-sample simulation runs. A full-sample simulation run calculates the models' Sharpe ratios from a randomly drawn sample of 618 months from the 618 months between July 1968 to December 2019. For the in- and out-of-sample simulations, the 618 months are split into 309 pairs of adjacent months, from which 309 pairs are randomly drawn with replacement. The in-sample simulation randomly selects one month of each pair based on which the models' maximum squared Sharpe ratios as well as the factors' weights in the models' tangency portfolios are calculated. The out-of-sample simulation calculates the models' maximum squared Sharpe ratios by using the factors' tangency weights from the respective in-sample simulation run and the factors' mean returns and covariance matrices from the unused months of the adjacent months. Beyond the models' mean and median maximum squared Sharpe ratios across the 100,000 simulation runs, Panel A also displays the percentage of simulation runs in which the enhanced model exhibits a higher maximum squared Sharpe ratio than the standard Fama-French (2015) model. Panel B displays for each model the factors' weights in the tangency portfolio across the sample period from July 1968 to December 2019.

Panel A: Maximum Sharpe Ratios

			Full Sample			In-Sample			Out-of-Sample		
Model	SR^2	BKRS	Mean	Median	Percent	Mean	Median	Percent	Mean	Median	Percent
Fama-French	0.093		0.104	0.102		0.114	0.111		0.087	0.083	
Enhanced	0.160	2.640	0.171	0.169	0.997	0.183	0.178	0.971	0.152	0.148	0.975

Panel B: Tangency Weights

Model	MP	SMB	HML	RMW	CMA
Fama-French	0.176	0.086	−0.030	0.304	0.465
Enhanced	0.114	0.082	0.058	0.368	0.378

Table 5
Factor Pricing

This table displays results from factor model regressions. In Panel A, the standard Fama-French (2015) five-factor model is used to explain the enhanced size (SMB*), value (HML*), profitability (RMW*), and investment (CMA*) factors. In Panel B, the enhanced five-factor model is used to explain the standard Fama-French (2015) size (SMB), value (HML), profitability (RMW), and investment (CMA) factors. The factors are constructed as described in Section 3.6. The sample period is from July 1968 to December 2019. α is in percent. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Pricing Enhanced Factors with Fama-French Factors

	α	β^{MP}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	R^2
SMB*	0.06***	0.00	0.97***	0.12***	0.02	0.05**	0.966
	(2.70)	(0.63)	(121.61)	(11.46)	(1.59)	(2.57)	
HML*	0.13**	0.01	0.10***	0.40***	−0.05	0.26***	0.495
	(2.07)	(0.45)	(4.46)	(13.33)	(−1.54)	(5.32)	
RMW*	0.22***	−0.01	−0.08***	−0.13***	0.46***	0.01	0.564
	(4.99)	(−1.20)	(−5.02)	(−6.21)	(22.43)	(0.15)	
CMA*	0.13***	−0.03***	0.04***	−0.09***	0.07***	0.64***	0.578
	(3.49)	(−3.65)	(3.16)	(−4.95)	(3.80)	(21.35)	

Panel B: Pricing Fama-French Factors with Enhanced Factors

	α	β^{MP^*}	β^{SMB^*}	β^{HML^*}	β^{RMW^*}	β^{CMA^*}	R^2
SMB	−0.08***	0.02***	0.99***	−0.07***	−0.02	−0.04*	0.953
	(−2.91)	(3.21)	(98.84)	(−4.55)	(−1.13)	(−1.95)	
HML	0.14	−0.10***	−0.07**	0.82***	−0.21***	0.10	0.479
	(1.60)	(−4.69)	(−2.14)	(18.11)	(−3.59)	(1.37)	
RMW	0.00	−0.05***	−0.05*	−0.03	0.98***	0.13**	0.522
	(0.03)	(−3.02)	(−1.92)	(−0.91)	(21.76)	(2.28)	
CMA	0.07	−0.06***	−0.03*	0.24***	−0.17***	0.68***	0.630
	(1.53)	(−5.47)	(−1.77)	(9.95)	(−5.29)	(17.50)	

Table 6
Spanning Regressions

Panel A of this table displays the results from spanning regressions that aim to explain each of the five standard Fama-French (2015) based on the respective other four factors. Panel B displays the same results for the enhanced factors. The factors are constructed as described in Section 3.6. The sample period is from July 1968 to December 2019. α is in percent. t-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fama-French Factors

	α	β^{MP}	β^{SMB}	β^{HML}	β^{RMW}	β^{CMA}	R^2
MP	0.85***		0.23***	0.11	−0.44***	−1.07***	0.240
	(5.26)		(4.05)	(1.40)	(−5.71)	(−8.84)	
SMB	0.20*	0.11***		0.01	−0.43***	−0.01	0.160
	(1.76)	(4.05)		(0.09)	(−8.28)	(−0.12)	
HML	−0.04	0.03	0.00		0.22***	1.09***	0.485
	(−0.46)	(1.40)	(0.09)		(5.48)	(22.12)	
RMW	0.39***	−0.12***	−0.24***	0.22***		−0.38***	0.213
	(4.67)	(−5.71)	(−8.28)	(5.48)		(−5.98)	
CMA	0.22***	−0.11***	0.00	0.41***	−0.14***		0.533
	(4.35)	(−8.84)	(−0.12)	(22.12)	(−5.98)		

Panel B: Enhanced Factors

	α	β^{MP^*}	β^{SMB^*}	β^{HML^*}	β^{RMW^*}	β^{CMA^*}	R^2
MP^*	0.93***		0.27***	−0.02	−0.41***	−1.27***	0.215
	(5.53)		(4.51)	(−0.27)	(−3.67)	(−9.63)	
SMB^*	0.29***	0.12***		0.23***	−0.64***	0.03	0.191
	(2.58)	(4.51)		(3.94)	(−9.07)	(0.37)	
HML^*	0.10	−0.01	0.11***		0.02	0.73***	0.258
	(1.26)	(−0.27)	(3.94)		(0.33)	(12.65)	
RMW^*	0.38***	−0.05***	−0.19***	0.01		−0.11**	0.161
	(6.43)	(−3.67)	(−9.07)	(0.33)		(−2.12)	
CMA^*	0.25***	−0.10***	0.01	0.29***	−0.07**		0.340
	(5.26)	(−9.63)	(0.37)	(12.65)	(−2.12)		

Table 7
Factor Risk Prices

This table displays average annualized risk premium estimates (in percent) from monthly cross-sectional Fama-MacBeth (1973) regressions. The regressions are estimated at the end of each month from June 1969 to December 2019 using all common US stocks traded on the NYSE, AMEX, or NASDAQ. The dependent variable is the compounded return across the previous 12 months in excess of the compounded one-month T-bill rate. The independent variables are a constant and betas with respect to the factors from the Fama-French (2015) five-factor model (Panel A) respectively the enhanced five-factor model (Panel B). Betas are estimated at the end of each month from multivariate time-series regressions that regress stocks' daily excess returns across the previous 12 months on the factor models. We require at least 100 daily observations to estimate the betas. All dependent and independent variables are in each month winsorized at the 0.5%- and 99.5%-level. Rows labelled "UV" display risk premium estimates from univariate Fama-MacBeth (1973) regressions that use only the constant and one of the betas as explanatory variables; Rows labelled "MV" display risk premium estimates from multivariate Fama-MacBeth (1973) regressions that use the constant and all betas as explanatory variables. Column "Method" displays the method used to estimate the monthly Fama-MacBeth (1973) regressions; "WLS" estimates the regressions using weighted least squares with stocks' market capitalizations as weights; "IV" estimates the regressions based on the instrumental variable approach described in Appendix B, which is also implemented using weighted least squares with stocks' market capitalizations as weights. Panel C displays the differences between the enhanced factors' risk premium estimates from Panel B and the Fama-French (2015) factors' risk premium estimates from Panel A. R^2 is the average adjusted R-squared of the monthly regressions. t-statistics are reported in parentheses and are computed using Newey-West (1987) heteroskedasticity-robust standard errors with 12 lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Risk Prices of Fama-French Factors

	Method	γ^{ZB}	γ^{MP}	γ^{SMB}	γ^{HML}	γ^{RMW}	γ^{CMA}	R^2
UV	WLS		8.06***	6.07***	−3.28***	−2.71	−0.87	
			(3.43)	(3.82)	(−2.67)	(−1.59)	(−0.85)	
UV	IV		8.20**	6.74***	−3.78**	−1.54	−0.06	
			(2.49)	(3.56)	(−2.15)	(−1.21)	(−0.05)	
MV	WLS	4.29***	9.68***	5.97***	−4.19***	−2.29	−0.98	0.313
		(2.61)	(3.63)	(4.03)	(−2.69)	(−1.45)	(−1.06)	
MV	IV	5.42***	5.88**	5.58***	−4.77***	−0.24	−0.25	0.245
		(2.60)	(2.28)	(3.24)	(−3.10)	(−0.18)	(−0.20)	

Panel B: Risk Prices of Enhanced Factors

	Method	γ^{ZB}	γ^{MP^*}	γ^{SMB^*}	γ^{HML^*}	γ^{RMW^*}	γ^{CMA^*}	R^2
UV	WLS		12.46***	7.99***	−1.05	1.51	0.96	
			(3.68)	(4.06)	(−1.01)	(1.20)	(1.15)	
UV	IV		10.30***	7.49***	−2.69	−0.68	1.76	
			(3.12)	(4.27)	(−1.41)	(−0.47)	(1.16)	
MV	WLS	2.77	11.25***	5.39***	0.05	0.35	1.43**	0.298
		(1.30)	(3.57)	(3.67)	(0.05)	(0.41)	(2.45)	
MV	IV	1.45	8.82***	4.97***	−1.60	2.13*	3.62***	0.235
		(0.54)	(3.19)	(2.71)	(−1.06)	(1.91)	(3.15)	

Panel C: Difference in Risk Prices

	Method	γ^{ZB}	γ^{MP^*}	γ^{SMB^*}	γ^{HML^*}	γ^{RMW^*}	γ^{CMA^*}	R^2
UV	WLS		4.40	1.92	2.23*	4.22*	1.83***	
			(1.55)	(1.38)	(1.93)	(1.67)	(2.82)	
UV	IV		1.58	0.97	1.39	0.29	1.65	
			(0.80)	(0.83)	(0.98)	(0.25)	(1.25)	
MV	WLS	−1.52	1.57	−0.58	4.24***	2.64	2.41***	−0.015
		(−1.26)	(1.31)	(−1.54)	(2.59)	(1.59)	(3.30)	
MV	IV	−3.97	2.62	−0.60	2.94**	2.19*	4.16***	−0.010
		(−1.58)	(1.43)	(−0.82)	(2.02)	(1.78)	(3.72)	

Table 8
Comparison with Hedged Factors

Panel A of this table displays results for the hedged market ($\mathrm{MP^H}$), size ($\mathrm{SMB^H}$), value ($\mathrm{HML^H}$), profitability ($\mathrm{RMW^H}$), and investment ($\mathrm{CMA^H}$) factors. Mean returns, volatilities, and alphas are in percent. α^{SR} are intercepts from spanning regressions that explain each of the factors based on the respective other four factors. The panel also displays statistics on the comparison between the enhanced factors and the corresponding hedged factors: "Diff" shows the difference in mean returns; "Corr" shows the correlation; "dSR" shows the difference in Sharpe ratios; α^H (α^*) are intercepts from regressions that explain the hedged (enhanced) factors with the enhanced (hedged) five-factor model. Panel B displays the same results for the enhanced hedged market ($\mathrm{MP^{H^*}}$), size ($\mathrm{SMB^{H^*}}$), value ($\mathrm{HML^{H^*}}$), profitability ($\mathrm{RMW^{H^*}}$), and investment ($\mathrm{CMA^{H^*}}$) factors. It compares the enhanced hedged factors to their hedged counterparts. α^{H*} (α^H) are intercepts from regressions that explain the enhanced hedged (hedged) factors with the hedged (enhanced hedged) five-factor model. Panel C displays results on the Sharpe ratios of the hedged, enhanced, and enhanced hedged five-factor models. "SR^2" is the maximum monthly squared Sharpe ratio across the sample period. "BKRS" is the test statistic from testing whether the models' maximum squared Sharpe ratio is equal to the hedged model's maximum squared Sharpe ratio. The remaining columns display mean and median Sharpe ratios from 100,000 full-sample, in-sample, and out-of-sample simulation runs which are conducted as described in Table 4. The panel also displays the percentage of simulation runs in which the models exhibit higher maximum squared Sharpe ratios than the hedged model. Panel D displays annualized risk premium estimates (in percent) for the factors of the hedged and enhanced hedged factor models. The factors' risk premia are estimated from multivariate cross-sectional Fama-MacBeth (1973) regressions as described in Table 7. Column "Method" displays the method used to estimate the monthly Fama-MacBeth (1973) regressions; "WLS" estimates the regressions with weighted least squares with the stocks' market capitalizations as weights; "IV" estimates the regressions based on the instrumental variable approach described in Appendix B, which is also implemented using weighted least squares with the stocks' market capitalizations as weights. The panel also displays the differences between the risk premium estimates for the enhanced hedged factors and those for the hedged factors. R^2 is the average adjusted R-squared of the monthly regressions. In all panels, the sample period is from July 1968 to December 2019. t-statistics are reported in parentheses. t-statistics in Panel D are computed using Newey-West (1987) heteroskedasticity-robust standard errors with 12 lags.

Panel A: Hedged Factors

					Correlations					Comparison to Enhanced				
	Mean	Std	SR	α^{SR}	$\mathrm{MP^H}$	$\mathrm{SMB^H}$	$\mathrm{HML^H}$	$\mathrm{RMW^H}$	$\mathrm{CMA^H}$	Diff	Corr	dSR	α^H	α^*
$\mathrm{MP^H}$	0.52***	3.03	0.17	0.72***	1.000	−0.290	−0.176	0.166	−0.265	0.01	0.675	−0.06	0.21**	0.06
	(4.29)			(6.08)						(0.05)		(−1.30)	(2.32)	(0.45)
$\mathrm{SMB^H}$	0.12	1.95	0.06	0.30***		1.000	0.152	−0.308	0.136	0.14*	0.743	0.03	0.07	0.08
	(1.58)			(3.91)						(1.71)		(0.87)	(1.41)	(1.00)
$\mathrm{HML^H}$	0.25***	1.75	0.14	0.09			1.000	−0.478	0.669	0.08	0.422	0.01	0.28***	0.19**
	(3.57)			(1.59)						(0.92)		(0.27)	(4.49)	(2.29)
$\mathrm{RMW^H}$	0.16***	1.55	0.10	0.33***				1.000	−0.488	0.12**	0.652	0.08**	0.00	0.22***
	(2.59)			(6.24)						(2.30)		(2.34)	(−0.05)	(4.39)
$\mathrm{CMA^H}$	0.25***	1.28	0.19	0.21***					1.000	0.03	0.449	0.00	0.21***	0.15***
	(4.76)			(5.51)						(0.54)		(0.11)	(4.41)	(2.82)

Panel B: Enhanced Hedged Factors

					Correlations					Comparison to Hedged				
	Mean	Std	SR	α^{SR}	$\mathrm{MP^{H^*}}$	$\mathrm{SMB^{H^*}}$	$\mathrm{HML^{H^*}}$	$\mathrm{RMW^{H^*}}$	$\mathrm{CMA^{H^*}}$	Diff	Corr	dSR	α^{H*}	α^H
$\mathrm{MP^{H^*}}$	0.56***	3.09	0.18	0.85***	1.000	−0.328	−0.280	0.129	−0.206	0.04	0.927	0.01	0.01	0.00
	(4.52)			(6.99)						(0.85)		(0.49)	(0.25)	(−0.06)
$\mathrm{SMB^{H^*}}$	0.21**	2.05	0.10	0.40***		1.000	0.235	−0.403	0.092	0.09**	0.891	0.04*	0.07*	−0.07*
	(2.54)			(5.10)						(2.25)		(1.93)	(1.67)	(−1.72)
$\mathrm{HML^{H^*}}$	0.30***	1.39	0.22	0.22***			1.000	−0.206	0.453	0.05	0.287	0.07	0.29***	0.21***
	(5.35)			(4.30)						(0.62)		(1.36)	(5.24)	(3.01)
$\mathrm{RMW^{H^*}}$	0.23***	1.23	0.19	0.29***				1.000	0.026	0.07	0.680	0.09**	0.16***	0.05
	(4.71)			(6.03)						(1.56)		(2.49)	(4.16)	(0.94)
$\mathrm{CMA^{H^*}}$	0.26***	1.04	0.25	0.14***					1.000	0.01	0.502	0.06	0.12***	0.14***
	(6.13)			(3.58)						(0.23)		(1.31)	(3.22)	(3.08)

Panel C: Maximum Sharpe Ratios

			Full Sample			In-Sample			Out-of-Sample		
Model	SR^2	BKRS	Mean	Median	Percent	Mean	Median	Percent	Mean	Median	Percent
Hedged	0.171		0.185	0.182		0.198	0.192		0.166	0.161	
Enhanced	0.160	−0.290	0.171	0.169	0.368	0.183	0.178	0.401	0.152	0.148	0.401
Enhanced Hedged	0.235	1.799	0.248	0.245	0.960	0.260	0.255	0.883	0.228	0.223	0.891

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Panel D: Risk Prices

Model	Method	γ^{ZB}	$\gamma^{MP^{\mathrm{H}}}$	$\gamma^{SMB^{\mathrm{H}}}$	$\gamma^{HML^{\mathrm{H}}}$	$\gamma^{RMW^{\mathrm{H}}}$	$\gamma^{CMA^{\mathrm{H}}}$	R^2
Hedged	WLS	4.92***	5.54***	0.74	−1.19	−2.37*	1.11	0.279
		(2.82)	(3.24)	(0.68)	(−1.23)	(−1.95)	(1.59)	
Hedged	IV	5.01	6.24**	1.45	−2.33	−2.28**	2.58**	0.217
		(1.56)	(2.29)	(0.98)	(−1.48)	(−2.01)	(2.15)	
Enhanced Hedged	WLS	5.72***	5.84***	0.17	1.99	−0.76	0.81	0.266
		(3.09)	(2.89)	(0.13)	(1.39)	(−0.96)	(1.22)	
Enhanced Hedged	IV	7.32*	4.05	−0.93	3.46***	0.15	6.57***	0.211
		(1.73)	(1.45)	(−0.57)	(2.65)	(0.14)	(6.89)	
Difference	WLS	0.80	0.30	−0.57	3.17**	1.61	−0.30	−0.013
		(0.92)	(0.24)	(−1.16)	(2.04)	(1.32)	(−0.42)	
Difference	IV	2.31	−2.34	−1.90	5.89***	2.00	5.02***	−0.006
		(0.63)	(−1.09)	(−1.36)	(2.76)	(1.59)	(3.38)	

Table 9
Comparison with Cross-Section Factors

Panel A of this table displays results for the cross-section market (MP^{CS}), size (SMB^{CS}), value (HML^{CS}), profitability (RMW^{CS}), and investment (CMA^{CS}) factors. Mean returns, volatilities, and alphas are in percent. α^{SR} are intercepts from spanning regressions that explain each of the factors based on the respective other four factors. The panel also displays statistics on the comparison between the enhanced factors and the corresponding cross-section factors: "Diff" shows the difference in mean returns; "Corr" shows the correlation; "dSR" shows the difference in Sharpe ratios; α^{CS} (α^{*}) are intercepts from regressions that explain the cross-section (enhanced) factors with the enhanced (cross-section) five-factor model. Panel B displays the same results for the enhanced cross-section market ($\text{MP}^{\text{CS*}}$), size ($\text{SMB}^{\text{CS*}}$), value ($\text{HML}^{\text{CS*}}$), profitability ($\text{RMW}^{\text{CS*}}$), and investment ($\text{CMA}^{\text{CS*}}$) factors. It compares the enhanced cross-section factors to their cross-section counterparts. α^{CS*} (α^{CS}) are intercepts from regressions that explain the enhanced cross-section (cross-section) factors with the cross-section (cross-section) five-factor model. Panel C displays results on the Sharpe ratios of the cross-section, enhanced, and enhanced cross-section five-factor models. "SR^2" is the maximum monthly squared Sharpe ratio across the sample period. "BKRS" is the test statistic from testing whether the models' maximum squared Sharpe ratio is equal to the cross-section model's maximum squared Sharpe ratio. The remaining columns display mean and median Sharpe ratios from 100,000 full-sample, in-sample, and out-of-sample simulation runs which are conducted as described in Table 4. The panel also displays the percentage of simulation runs in which the models exhibit higher maximum squared Sharpe ratios than the cross-section model. Panel D displays annualized risk premium estimates (in percent) for the factors of the cross-section and enhanced cross-section factor models. The factors' risk premia are estimated from multivariate cross-sectional Fama-MacBeth (1973) regressions as described in Table 7. Column "Method" displays the method used to estimate the monthly Fama-MacBeth (1973) regressions; "WLS" estimates the regressions with weighted least squares with the stocks' market capitalizations as weights; "IV" estimates the regressions based on the instrumental variable approach described in Appendix B, which is also implemented using weighted least squares with the stocks' market capitalizations as weights. The panel also displays the differences between the risk premium estimates for the enhanced cross-section factors and those for the cross-section factors. R^2 is the average adjusted R-squared of the monthly regressions. In all panels, the sample period is from July 1968 to December 2019. t-statistics are reported in parentheses. t-statistics in Panel D are computed using Newey-West (1987) heteroskedasticity-robust standard errors with 12 lags.

Panel A: Cross-Section Factors

					Correlations					Comparison to Enhanced				
	Mean	Std	SR	α^{SR}	MP^{CS}	SMB^{CS}	HML^{CS}	RMW^{CS}	CMA^{CS}	Diff	Corr	dSR	α^{CS}	α^{*}
MP^{CS}	0.53***	4.49	0.12	0.91***	1.000	0.267	−0.268	−0.271	−0.454	0.00	1.000	0.00	0.00	0.00
	(2.93)			(5.79)								(0.00)	(0.00)	(0.00)
SMB^{CS}	0.08	1.50	0.05	0.08		1.000	−0.346	−0.286	−0.097	0.18***	0.941	0.04**	−0.04*	0.04
	(1.29)			(1.32)						(2.84)		(2.16)	(−1.90)	(1.26)
HML^{CS}	0.09**	1.02	0.09	0.00			1.000	0.710	0.164	0.24***	0.585	0.06	0.05	0.11*
	(2.26)			(−0.07)						(3.41)		(1.55)	(1.38)	(1.74)
RMW^{CS}	0.10***	0.73	0.14	0.07***				1.000	0.120	0.18***	0.447	0.04	0.02	0.20***
	(3.54)			(3.41)						(3.16)		(0.77)	(0.82)	(4.41)
CMA^{CS}	0.07***	0.41	0.17	0.09***					1.000	0.21***	0.618	0.03	0.03**	0.13***
	(4.22)			(6.01)						(4.28)		(0.75)	(2.00)	(3.09)

Panel B: Enhanced Cross-Section Factors

					Correlations					Comparison to Cross-Section				
	Mean	Std	SR	α^{SR}	$\text{MP}^{\text{CS*}}$	$\text{SMB}^{\text{CS*}}$	$\text{HML}^{\text{CS*}}$	$\text{RMW}^{\text{CS*}}$	$\text{CMA}^{\text{CS*}}$	Diff	Corr	dSR	α^{CS*}	α^{CS}
$\text{MP}^{\text{CS*}}$	0.53***	4.49	0.12	0.91***	1.000	0.213	−0.142	−0.095	−0.310	0.00	1.000	0.00	0.00	0.00
	(2.93)			(5.44)								(0.00)	(0.00)	(0.00)
$\text{SMB}^{\text{CS*}}$	0.14**	1.45	0.10	0.11*		1.000	−0.089	−0.019	−0.039	0.07***	0.944	0.05***	0.03*	−0.03
	(2.45)			(1.83)						(3.29)		(2.99)	(1.84)	(−1.38)
$\text{HML}^{\text{CS*}}$	0.06**	0.61	0.10	0.12***			1.000	−0.036	−0.200	−0.03	0.609	0.01	0.01	0.04
	(2.41)			(4.82)						(−1.02)		(0.14)	(0.50)	(1.25)
$\text{RMW}^{\text{CS*}}$	0.08***	0.49	0.16	0.12***				1.000	−0.340	−0.03	0.506	0.02	0.05***	0.02
	(4.00)			(6.61)						(−0.98)		(0.42)	(3.23)	(0.88)
$\text{CMA}^{\text{CS*}}$	0.03**	0.37	0.09	0.08***					1.000	−0.04**	0.543	−0.08**	0.02	0.03**
	(2.29)			(6.46)						(−2.39)		(−2.14)	(1.36)	(2.34)

Panel C: Maximum Sharpe Ratios

			Full Sample			In-Sample			Out-of-Sample		
Model	SR^2	BKRS	Mean	Median	Percent	Mean	Median	Percent	Mean	Median	Percent
CS	0.113		0.124	0.122		0.135	0.131		0.106	0.102	
Enhanced	0.160	1.762	0.171	0.169	0.962	0.183	0.178	0.891	0.152	0.148	0.897
Enhanced CS	0.138	1.038	0.150	0.148	0.852	0.162	0.157	0.769	0.131	0.127	0.769

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Panel D: Risk Prices								
Model	Method	γ^{ZB}	$\gamma^{MP^{\text{CS}}}$	$\gamma^{SMB^{\text{CS}}}$	$\gamma^{HML^{\text{CS}}}$	$\gamma^{RMW^{\text{CS}}}$	$\gamma^{CMA^{\text{CS}}}$	R^2
Cross-Section	WLS	3.94**	10.04***	2.88***	−1.61***	−1.00*	−0.29	0.310
		(2.36)	(3.73)	(4.00)	(−2.86)	(−1.73)	(−1.41)	
Cross-Section	IV	5.08**	6.72**	2.56***	−1.19**	−0.16	−0.05	0.243
		(2.47)	(2.56)	(2.94)	(−2.28)	(−0.33)	(−0.18)	
Enhanced CS	WLS	2.45	11.57***	2.67***	−0.15	0.35	0.11	0.298
		(1.13)	(3.63)	(3.82)	(−0.49)	(1.22)	(0.59)	
Enhanced CS	IV	1.44	8.57***	2.72***	−0.92**	0.85**	0.66**	0.235
		(0.51)	(3.11)	(2.93)	(−2.40)	(2.47)	(2.28)	
Difference	WLS	−1.49	1.53	−0.21	1.45**	1.35**	0.40**	−0.013
		(−1.26)	(1.31)	(−0.77)	(2.35)	(2.30)	(2.06)	
Difference	IV	−3.65	2.02	0.20	0.21	0.89*	0.81**	−0.008
		(−1.40)	(1.10)	(0.40)	(0.42)	(1.75)	(2.32)	

Table 10
Comparison with Time-Series Efficient Factors

Panel A of this table displays results for the time-series efficient market ($\mathrm{MP^{TE}}$), size ($\mathrm{SMB^{TE}}$), value ($\mathrm{HML^{TE}}$), profitability ($\mathrm{RMW^{TE}}$), and investment ($\mathrm{CMA^{TE}}$) factors. Mean returns, volatilities, and alphas are in percent. α^{SR} are intercepts from spanning regressions that explain each of the factors based on the respective other four factors. The panel also displays statistics on the comparison between the enhanced factors and the corresponding time-series efficient factors: "Diff" shows the difference in mean returns; "Corr" shows the correlation; "dSR" shows the difference in Sharpe ratios; α^{TE} (α^{*}) are intercepts from regressions that explain the time-series efficient (enhanced) factors with the enhanced (time-series efficient) five-factor model. Panel B displays the same results for the enhanced time-series efficient market ($\mathrm{MP^{TE*}}$), size ($\mathrm{SMB^{TE*}}$), value ($\mathrm{HML^{TE*}}$), profitability ($\mathrm{RMW^{TE*}}$), and investment ($\mathrm{CMA^{TE*}}$) factors. It compares the enhanced time-series efficient factors to their time-series efficient counterparts. α^{TE*} (α^{TE}) are intercepts from regressions that explain the enhanced time-series efficient (time-series efficient) factors with the time-series efficient (time-series efficient) five-factor model. Panel C displays results on the Sharpe ratios of the time-series efficient, enhanced, and enhanced time-series efficient five-factor models. "$\mathrm{SR^2}$" is the maximum monthly squared Sharpe ratio across the sample period. "BKRS" is the test statistic from testing whether the models' maximum squared Sharpe ratio is equal to the time-series efficient model's maximum squared Sharpe ratio. The remaining columns display mean and median Sharpe ratios from 100,000 full-sample, in-sample, and out-of-sample simulation runs which are conducted as described in Table 4. The panel also displays the percentage of simulation runs in which the models exhibit higher maximum squared Sharpe ratios than the time-series efficient model. Panel D displays annualized risk premium estimates (in percent) for the factors of the time-series efficient and enhanced time-series efficient factor models. The factors' risk premia are estimated from multivariate cross-sectional Fama-MacBeth (1973) regressions as described in Table 7. Column "Method" displays the method used to estimate the monthly Fama-MacBeth (1973) regressions; "WLS" estimates the regressions with weighted least squares with the stocks' market capitalizations as weights; "IV" estimates the regressions based on the instrumental variable approach described in Appendix B, which is also implemented using weighted least squares with the stocks' market capitalizations as weights. The panel also displays the differences between the risk premium estimates for the enhanced time-series efficient factors and those for the time-series efficient factors. R^2 is the average adjusted R-squared of the monthly regressions. In all panels, the sample period is from July 1968 to December 2019. t-statistics are reported in parentheses. t-statistics in Panel D are computed using Newey-West (1987) heteroskedasticity-robust standard errors with 12 lags.

Panel A: Time-Series Efficient Factors

					Correlations					Comparison to Enhanced				
	Mean	Std	SR	α^{SR}	$\mathrm{MP^{TE}}$	$\mathrm{SMB^{TE}}$	$\mathrm{HML^{TE}}$	$\mathrm{RMW^{TE}}$	$\mathrm{CMA^{TE}}$	Diff	Corr	dSR	α^{TE}	α^{*}
$\mathrm{MP^{TE}}$	0.31***	2.61	0.12	0.50***	1.000	0.142	−0.220	−0.324	−0.229	0.22*	0.726	0.00	0.14*	0.36***
	(2.98)			(5.02)						(1.74)		(−0.04)	(1.75)	(2.86)
$\mathrm{SMB^{TE}}$	0.14**	1.82	0.08	0.14*		1.000	0.019	−0.160	−0.005	0.11	0.752	0.01	0.07	0.11
	(1.97)			(1.87)						(1.46)		(0.35)	(1.42)	(1.39)
$\mathrm{HML^{TE}}$	0.33***	1.82	0.18	0.07			1.000	0.309	0.672	−0.01	0.599	−0.03	0.22***	0.10
	(4.51)			(1.24)						(−0.11)		(−0.71)	(3.52)	(1.46)
$\mathrm{RMW^{TE}}$	0.27***	1.49	0.18	0.27***				1.000	0.182	0.01	0.533	0.00	0.11**	0.21***
	(4.49)			(4.74)						(0.23)		(0.07)	(2.11)	(4.08)
$\mathrm{CMA^{TE}}$	0.20***	1.19	0.17	0.09**					1.000	0.07	0.623	0.03	0.09**	0.16***
	(4.21)			(2.35)						(1.59)		(0.74)	(2.31)	(3.57)

Panel B: Enhanced Time-Series Efficient Factors

					Correlations					Comparison to Time-Series Efficient				
	Mean	Std	SR	α^{SR}	$\mathrm{MP^{TE*}}$	$\mathrm{SMB^{TE*}}$	$\mathrm{HML^{TE*}}$	$\mathrm{RMW^{TE*}}$	$\mathrm{CMA^{TE*}}$	Diff	Corr	dSR	α^{TE*}	α^{TE}
$\mathrm{MP^{TE*}}$	0.33***	3.11	0.11	0.66***	1.000	0.130	−0.194	−0.210	−0.396	0.02	0.947	−0.01	0.06	0.00
	(2.66)			(5.59)						(0.46)		(−0.94)	(1.44)	(0.11)
$\mathrm{SMB^{TE*}}$	0.17**	2.12	0.08	0.17**		1.000	0.141	−0.287	0.071	0.02	0.938	0.00	0.01	0.00
	(1.97)			(1.96)						(0.78)		(0.01)	(0.35)	(0.15)
$\mathrm{HML^{TE*}}$	0.28***	1.63	0.17	0.08			1.000	0.068	0.475	−0.06	0.660	−0.01	0.06	0.15***
	(4.21)			(1.38)						(−0.95)		(−0.35)	(1.29)	(2.68)
$\mathrm{RMW^{TE*}}$	0.24***	1.16	0.21	0.26***				1.000	0.106	−0.03	0.602	0.03	0.15***	0.09*
	(5.15)			(5.71)						(−0.61)		(0.86)	(4.12)	(1.83)
$\mathrm{CMA^{TE*}}$	0.23***	1.05	0.22	0.18***					1.000	0.03	0.707	0.05	0.12***	0.04
	(5.43)			(4.96)						(0.80)		(1.61)	(3.99)	(1.06)

Panel C: Maximum Sharpe Ratios

			Full Sample			In-Sample			Out-of-Sample		
Model	$\mathrm{SR^2}$	BKRS	Mean	Median	Percent	Mean	Median	Percent	Mean	Median	Percent
TE	0.110		0.120	0.118		0.131	0.127		0.102	0.098	
Enhanced	0.160	1.429	0.171	0.169	0.923	0.183	0.178	0.841	0.152	0.148	0.858
Enhanced TE	0.157	1.659	0.168	0.166	0.952	0.178	0.174	0.876	0.148	0.144	0.892

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Panel D: Risk Prices

Model	Method	γ^{ZB}	$\gamma^{MP^{\mathrm{TE}}}$	$\gamma^{SMB^{\mathrm{TE}}}$	$\gamma^{HML^{\mathrm{TE}}}$	$\gamma^{RMW^{\mathrm{TE}}}$	$\gamma^{CMA^{\mathrm{TE}}}$	R^2
Time-Series Efficient	WLS	7.33***	1.94*	1.57**	−0.87**	−0.46	−0.35*	0.283
		(4.76)	(1.76)	(2.48)	(−2.05)	(−1.40)	(−1.85)	
Time-Series Efficient	IV	9.11***	0.02	1.33	−1.28**	0.22	−0.57**	0.223
		(3.73)	(0.01)	(1.59)	(−2.39)	(0.51)	(−2.22)	
Enhanced TE	WLS	7.36***	3.73**	2.31***	0.16	0.15	−0.06	0.272
		(4.30)	(2.15)	(2.63)	(0.36)	(0.55)	(−0.28)	
Enhanced TE	IV	5.52*	1.98	3.29***	−1.43**	1.28***	0.46	0.217
		(1.66)	(1.01)	(3.20)	(−2.37)	(2.76)	(1.56)	
Difference	WLS	0.02	1.79	0.74	1.03**	0.61*	0.29***	−0.011
		(0.04)	(1.45)	(1.54)	(2.40)	(1.72)	(2.59)	
Difference	IV	−3.59	2.62*	1.97***	−0.04	1.06**	1.16***	−0.006
		(−1.33)	(1.66)	(2.72)	(−0.05)	(2.13)	(3.50)	