Journal of Financial Economics 151 (2024) 103746

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

The use of asset growth in empirical asset pricing models ☆

Michael Cooper [a,*], Huseyin Gulen [b], Mihai Ion [c]

[a] The University of Utah, 1645 E. Campus Dr., Salt Lake City, UT 84112, United States of America
[b] Purdue University, United States of America
[c] University of Arizona, United States of America

ARTICLE INFO

Dataset link: https://doi.org/10.17632/tzxtm6ys99.1

JEL classification:
G12
G20

Keywords:
Anomalies
Factor model
Asset growth
Investment
The q-factor model
Dividend discount model
Overextrapolation

ABSTRACT

We show that the performance of the new factor models of Hou et al. (2015) and Fama and French (2015) depends crucially on how their investment factor is constructed. Both models use growth in total assets to measure investment. Their ability to price the cross-section of returns decreases significantly when the investment factor is constructed using traditional investment measures, or measures that also account for investment in intangibles. In contrast, we find that factors based on growth in inventory and accounts receivable contain the bulk of the pricing information in the asset growth factor. We show evidence that the superior performance of the asset growth factor seems to be attributable to its ability to capture aggregate shocks to equity financing costs.

1. Introduction

Recent advances in empirical factor models such as the four-factor model of Hou et al. (2015) and the five-factor model of Fama and French (2015) have improved our ability to explain the cross-section of equity returns, including the returns of many anomalies. As a result, these models have been widely adopted in the literature in the short period since their publication.[1] In these new models, the improvement relative to prior models such as the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model has come in part from the addition of new factors related to firm-level profitability and investment. In both Fama and French (2015) and Hou et al. (2015), the motivation to use profitability and investment factors is based on theoretical arguments (a dividend discount model for the five factor model and a production based model of Cochrane (1991) for the four factor model) that profitability and investment are inextricably linked to expected returns.

Our paper examines the link between the empirical specification and theoretical motivation of the investment factors in Hou, Xue, and Zhang (2015; hereafter HXZ) and Fama and French (2015; hereafter FF5F). Specifically, we call attention to the fact that the investment factors used in the empirical tests of both HXZ and FF5F are not based on traditional measures of firm investment (such as measures based on capital expenditures and the growth in property, plant, and equipment (PPE)) as one might expect from their theoretical arguments. Instead, both papers use "asset growth" (i.e., the year-on-year percentage change in the book value total assets) from Cooper et al. (2008) as a measure of investment. We show that both HXZ and FF5F factor models

☆ Nikolai Roussanov was the editor for this article. We are grateful for detailed and constructive feedback from an anonymous referee and the editor. This paper has also benefited from comments and discussions with Daniel Andrei, Adem Atmaz, Turan Bali, Hank Bessembinder, Stefano Cassella, Scott Cederburg, Sergey Chernenko, Tarun Chordia, Kent Daniel, David Denis, Theodore Goodman, Cam Harvey, Kate Holland, Greg Kadlec, Leonid Kogan, Karl Lins, Yan Liu, Rene Stulz, Michael Woeppel, Irene Yi, and seminar participants at Arizona State University, Bocconi University, Georgia State University, George Washington University, NOVA School of Business and Economics, Purdue University, Southern Methodist University, Texas Tech University, and Tulane University. We thank Mitchell Johnston for excellent research assistance.

* Corresponding author.
E-mail addresses: mike.cooper@eccles.utah.edu (M. Cooper), hgulen@purdue.edu (H. Gulen), mihaiion@email.arizona.edu (M. Ion).

[1] As of this writing, according to Google Scholar, FF5F had 7722 citations, and HXZ had 2347 citations.

https://doi.org/10.1016/j.jfineco.2023.103746
Received 19 August 2022; Received in revised form 28 October 2023; Accepted 28 October 2023
Available online 15 November 2023

derive much of their explanatory power from their nonconventional empirical specification for investment (i.e., asset growth). That is, these models are no more powerful than prior models they are purported to replace when conventional measures of investment are employed. Thus, despite the empirical power of these models and their potential relevance to performance evaluation, their relevance to asset pricing is potentially limited by their (lack of) theoretical justification, as is the case with many other firm characteristics associated with anomalous returns.

We argue that it is difficult to justify asset growth as the preferred measure of a firm's investment activity in the HXZ and FF5F models for several reasons. First, it is not at all clear that asset growth is the appropriate measure of investment in the context of the theoretical models used by FF5F and HXZ because these models do not provide strict guidelines as to which particular set of characteristics is best suited for constructing the new factors. This is primarily because they are reduced-form models which connect expected returns with a set of unobservable characteristics – expected growth in book-equity and expected profitability in FF5F, and optimal investment and expected profitability in HXZ. These unobservable characteristics do not have a clear link to the data.[2] Second, asset growth does not include off-balance sheet intangible capital, such as knowledge capital and organizational capital, an increasingly important type of capital that arguably should be included in an investment measure given recent evidence in Peters and Taylor (2017). Third, asset growth confounds investments with the financing used for them. For example, if a firm uses cash to finance an investment in PPE, we would observe zero growth in total assets when an investment was clearly made. Fourth, it is not clear to what extent growth in certain components of total assets, such as growth in current assets, can be classified as an investment activity. While increases in current assets could be indicative of the firm growing its operations, they can also be a result of the firm stagnating. Cash balances can increase in the absence of investment opportunities, inventory can increase if the firm is not able to sell its products at the same rate, and accounts receivables can increase if the firm is not able to recover the trade credit extended to its customers.

Motivated by these concerns with the asset growth (AG) measure, we conduct tests to determine how the HXZ and FF5 models perform when their AG factor is constructed using other common measures of investment. We start by building investment factors using the percentage growth in PPE, capital expenditures (CAPX) divided by lagged total assets, and arguably more complete measures of investments such as the ones proposed by Peters and Taylor (2017) which include investments in off-balance sheet intangible assets. We use a variety of performance metrics to compare the HXZ and FF5F models with analogous models that use our alternative investment factors.[3] Across all of our performance measures, our tests show that the performance of the HXZ and FF5F models decreases significantly if the AG factor was constructed using alternative measures of investment. This finding generalizes to a significantly broader set of investment measures. In a model-mining exercise, we construct 144 different combinations of investments in various types of assets (e.g., inventory, PPE, goodwill, R&D, SGA), and we find that all (almost all) of them underperform the AG-based HXZ (FF5F) model. The fact that neither conventional nor broader measures of investment perform as well as the AG-based factor reinforces our belief that this factor is not primarily about investment. Hence, using the standard q-theory as the motivation for the investment factor may be misplaced.

To gain a deeper understanding of what may be driving the pricing power of the AG factor, we decompose growth in total assets into its major subcomponents from both sides of the balance sheet and measure how/if the performance of the HXZ and FF5F models changes when we replace the AG factor with a factor based on one of the subcomponents. From the left-hand side of the balance sheet, we create factors based on changes in cash, inventory, accounts receivable, property, plant, and equipment (PPE), intangibles, and other assets (i.e., total assets minus the previous five categories). On the right-hand side, we develop factors using changes in current operating liabilities, non-current operating liabilities, long-term debt, common equity, and retained earnings. This gives us eleven different alternative versions of the HXZ and FF5F models, one for each subcomponent of AG.

Our comparison tests yield two main findings that are consistent across HXZ and FF5F comparisons. First, the models using an investment factor based on more traditional measures of investment such as growth in PPE or growth in balance-sheet intangibles significantly underperform the original AG-based models. Second, the models using growth in inventory (INVT) and growth in accounts receivable (AREC) do *not* perform significantly differently from the AG-based models. Motivated by these results, we use spanning regressions to show that the INVT and AREC factors (together) contain the bulk of the pricing information that the AG factor contributes to the HXZ and FF5F models. Furthermore, the AG, INVT, and AREC factors are not spanned by any other subcomponent of AG. These findings suggest that the explanatory power of the AG factor comes primarily from the information contained in the dynamics of accounts receivables and inventory, not PPE and intangible investments.

Despite their sensitivity to the way the AG factor is constructed, the HXZ and FF5F models (using AG as the investment factor) do perform well in describing the cross-section of stock returns. This means that the AG factor likely captures an aggregate source of comovement in returns that, given the results described above, is not captured by other measures of investment, but is captured by the INVT and AREC factors. To explore what this source of comovement might be, we use a representative set of macroeconomic variables that have been shown to produce cross-sectional risk dispersion in stock returns, and we use standard GMM tests to investigate whether they help price portfolios sorted on AG, INVT, AREC and PPE growth (beyond the market factor).[4]

The key finding revealed by these tests is that financing-related shocks (e.g., aggregate shocks to investor sentiment, equity-issuance costs, and financial intermediary balance sheets) help price AG, INVT, and AREC portfolios (though not always all three), but *not* PPE portfolios. The only factor that significantly helps price all three groups of AG, INVT, and AREC portfolios but not the PPE portfolios is the equity-market sentiment factor (BW) of Baker and Wurgler (2006). These results support the notion that the superior performance of the

[2] This point is summarized best in Kozak et al. (2019). Speaking primarily about HXZ, but making a point that applies equally to FF5F, on page 5, they argue: "In practice, however, neither expected profitability nor (planned) investment are observable. The usual approach is to use proxies, such as lagged profitability and lagged investment as potential predictors of unobserved quantities. Yet many additional characteristics are likely relevant for capturing expected profitability and planned investment and, therefore, expected returns. [...] The bottom line is that, in practice, q-theory does not necessarily provide much economic reason to expect sparse SDFs in the space of observable characteristics."

[3] Specifically, we compare models based on the number of anomalies explained, the number of significant alphas in a large set of test assets, and the maximum Sharpe ratio tests developed by Barillas and Shanken (2017).

[4] We use the following macroeconomic variables: the utilization-adjusted TFP shocks from Fernald (2012), the investment-specific technology factor from Papanikolaou (2011), an innovation factor based on Elsaify (2017), the consumption-wealth ratio from Lettau and Ludvigson (2001), the aggregate liquidity factor of Pastor and Stambaugh (2003), the macroeconomic uncertainty factor of Jurado et al. (2015), the measure of aggregate equity financing shocks from Belo et al. (2019), the financial intermediary leverage factor of Adrien et al. (2014), the financial intermediary capital ratio factor of He et al. (2017), the production network risk factor of Grigoris et al. (2023), the equity–market sentiment measure from Baker and Wurgler (2006), and the "high-yield share" measure used to proxy for credit–market sentiment in Greenwood and Hanson (2013).

AG, INVT, and AREC factors is likely linked to their ability to capture aggregate financing shocks (as in Belo et al., 2019; Adrien et al., 2014; He et al., 2017), particularly those driven by changes in equity-market sentiment. To tease out if the BW factor has independent pricing information with respect to the other aggregate factors, we repeat our GMM tests using three-factor SDFs, each a linear function of the market factor, the BW factor, and one of the remaining factors used in the prior test. We find that, for almost all SDF models, the BW factor still has a significant SDF loading when pricing AG, INVT, and AREC portfolios, but not when pricing PPE portfolios. Interestingly, when pricing AG, INVT, and AREC portfolios, almost all other macro factors become insignificant when BW is added to the SDF. This is not the case when pricing PPE portfolios, where, for example, the TFP, CAY, liquidity, and investment-specific technology shocks remain significant.

We argue that our findings are consistent with the debt-equity substitution mechanism proposed by Belo et al. (2019). The authors point out that firms with higher investment (measured as CAPX) should be less exposed to changes in equity-issuance costs because they are less collateral constrained than low-investment firms. This should allow these firms to better hedge against aggregate equity financing shocks by substituting equity for debt financing in bad states of the world. We point out that this mechanism should apply to all the other collateralizable assets of the firm. In particular, since short-term assets are more collateralizable than long-term assets [e.g., Berger et al. (1996)], sorting on INVT and AREC might provide more accurate sorts on the extent to which firms are collateral constrained. Supporting this interpretation, we show that, in periods with large decreases in investor sentiment (BW), firms with high AG, INVT, and AREC are more able to substitute equity for debt financing than firms with low AG, INVT, and AREC. We find that this substitutability is not as strong when we compare firms with high versus low PPE growth.

It is important to recognize that this debt-equity substitution channel can link the AG factor to equity financing costs regardless of what may be driving these costs. As detailed in Belo et al. (2019), equity financing costs may be driven by shocks to various forms of agency frictions or investor risk aversion, but they may also be driven by systemic behavioral biases. To investigate this possibility, we use an aggregate proxy for the degree of overextrapolation (DOX) in the economy from Cassella and Gulen (2018) and find that the superior performance of HXZ and FF5F over their analogues based on more traditional measures of investment is present only in high overextrapolation periods. In fact, in the subsample with below-median overextrapolation, the HXZ model does not perform significantly better than the Carhart (1997) four-factor model, and the FF5F model does not perform significantly better than the Fama and French (1993) model, or the Carhart (1997) model.

We acknowledge that it is difficult to definitively conclude that a given factor model captures risk or mispricing in the absence of a structural model. For this reason, we do not take a strong stance on which particular driver of equity financing costs is more likely to explain our results. Beyond our main finding that the AG factor seems to capture shocks to equity-issuance costs, the more general takeaway from our study is that linking reduced-form theoretical models (like the ones in Hou et al., 2015 and Fama and French, 2015) to the actual data is a tenuous endeavor, especially when those models include quantities that are not directly observable. The main allure of these kinds of models is that they provide a *parsimonious* potential theoretical explanation for return comovement patterns we observe in the data. However, as our paper shows, given the large number of degrees of freedom available when taking these models to the data, and the significant differences in performance caused by making different implementation choices, one has to question whether these reduced-form models are truly “disciplined by theory”. If they are not (as our results suggest), then there is little reason to prefer these models over statistically-motivated models such as Kozak et al. (2019) or Kelly et al. (2019).

2. Building factors using alternative measures of corporate investment

HXZ and FF5F show ample evidence that their models significantly outperform existing benchmark models (like Fama and French (1993) and Carhart (1997)) in explaining anomaly returns and the average returns of various tests assets.[5] The key finding that motivates our study is the observation that the performance of the HXZ and FF5F models deteriorates significantly if the AG factor is constructed using different measures of investment. To illustrate this fact, we begin by identifying some of the most common measures of corporate investment used in the literature. The corporate investment literature is vast, and any survey of it is bound to be incomplete. With this caveat in mind, our broad review of the literature reveals that empirical studies of corporate investment (including tests of the q-theory) most commonly focus on investment in physical capital, measured either using the capital expenditure (CAPX) figure from the statement of cash flows or growth in property, plant, and equipment (PPE).[6] Hence, we use CAPX and change in PPE, both divided by lagged PPE, as our two traditional measures of investment.[7]

In a recent study, Peters and Taylor (2017) point out that although firms mainly owned physical capital when the neoclassical theory of investment was developed more than three decades ago, intangible capital has become an increasingly important factor of production and should be included in measures of corporate investment. They calculate total intangible capital as the sum of intangible capital on the balance sheet (goodwill) plus intangible capital off the balance sheet. The latter is calculated as capitalized knowledge capital (R&D) plus capitalized organizational capital (30% of SG&A).[8] The total capital of a firm is calculated as the sum of physical capital (gross PPE) plus intangible capital. In our analysis below, we use the annual change in these measures of total, tangible and intangible capital as additional measures of investment (all normalized by lagged total capital). We refer to these measures as TOTK, PHK, and INTK respectively.[9]

[5] We replicate these findings in Section A and Tables E1 and E2 of the Appendix.

[6] Table E3 in the Appendix provides a sample of studies using CAPX or PPE growth to measure investment. This list is by no means exhaustive. Our only intent is to point out that, at least from our reading of the literature, standard practice seems to measure investment using CAPX and PPE-based variables. For comparison, in our search, we found only three studies that use growth in total assets to measure corporate investment – Alti and Tetlock (2014), Li and Zhang (2010), and Baker et al. (2003) – and the latter two use it as part of a larger set of investment measures.

[7] In unreported tests, we verify that our results are qualitatively unchanged if we use variations of these two measures, such as (1) normalizing by lagged total assets instead of PPE (e.g., Warusawitharana and Whited, 2016) (2) normalizing by replacement value of capital calculated using a perpetual inventory method (e.g., Fazzari et al., 1988) (3) subtracting the sale of PPE to obtain measures of net investment instead of gross investment (e.g., Liu et al., 2009) (4) adding R&D expense to all investment measures (e.g., Asker et al., 2015) (5) adding change in inventory to all investment measures (e.g., Lyandres et al., 2008) and (6) using capital expenditures net of depreciation (e.g., Denis and Sibilkov, 2010).

[8] The assumption that firms on average use 30% of SG&A as an investment in human capital and the rest for operating expenses has been used in several other studies e.g., Eisfeldt and Papanikolaou (2014), Hulten and Hao (2008), and Zhang (2014).

[9] Appendix C contains a discussion of the relation between asset growth and all of our alternative measures of investment. Table E4 in the Appendix shows that, just like AG, these measures also strongly negatively predict future stock returns, but AG remains a significant predictor when included in the same regressions. Table E5 shows, among other things, that AG provides an incomplete picture of firms' investment activity: a large portion (34% to 54%) of firms' total capital is not on the balance sheet, and the correlation between AG and off-balance sheet capital investment is quite low (around 0.16 to 0.30). See Appendix C for more details.

Table 1
Using Sharpe Ratio Tests to Compare HXZ and FF5F to Models Based on Alternative Investment Factors.

Panel A: Comparing HXZ-like models using maximum Sharpe ratio tests

Baseline model	Statistic	None	CAPX	PPE	TOTK	PHK	INTK
HXZ(AG)	$\Delta(maxSR^2)$	-0.078***	-0.038**	-0.044**	-0.040**	-0.055***	-0.055**
	p-value	(0.002)	(0.041)	(0.012)	(0.020)	(0.005)	(0.015)
None	$\Delta(maxSR^2)$		0.040**	0.034**	0.038**	0.023*	0.024*
	p-value		(0.016)	(0.035)	(0.030)	(0.094)	(0.053)
FF3F	$\Delta(maxSR^2)$	0.026	0.067**	0.060**	0.065**	0.049*	0.050*
	p-value	(0.303)	(0.023)	(0.032)	(0.021)	(0.070)	(0.074)

Panel B: Comparing FF5F-like models using maximum Sharpe ratio

Baseline model	Statistic	None	CAPX	PPE	TOTK	PHK	INTK
FF5F(AG)	$\Delta(maxSR^2)$	-0.037**	-0.034**	-0.038**	-0.037**	-0.033**	-0.039**
	p-value	(0.037)	(0.034)	(0.021)	(0.021)	(0.038)	(0.034)
None	$\Delta(maxSR^2)$		0.002	-0.001	-0.001	0.004	-0.002
	p-value		(0.698)	(0.664)	(0.782)	(0.573)	(0.331)
FF3F	$\Delta(maxSR^2)$	0.025	0.027	0.024	0.024	0.029	0.023
	p-value	(0.124)	(0.144)	(0.162)	(0.162)	(0.112)	(0.153)

Note: This table compares the performance of the HXZ and FF5F models with that of models based on alternative investment measures using maximum Sharpe ratio tests as in Barillas et al. (2020). The alternative measures of investment we use are: capital expenditures divided by lagged PPE ("CAPX" column), the percentage growth in PPE ("PPE" column), the percentage growth in total capital ("TOTK" column), the change in total physical capital divided by lagged total capital ("PHK" column), and the change in total intangible capital divided by lagged total capital ("INTK" column). For the last three measures, total capital, total physical capital, and total intangible capital are measured as in Peters and Taylor (2017). The Panel A constructs factors as in HXZ and Panel B constructs models as in FF5F. Columns and rows labeled "None" use no investment factor at all.

2.1. Using Sharpe ratio tests to compare model performance

We perform formal comparison tests between models with alternative constructions of the investment factor using the framework in Barillas and Shanken (2017) and Barillas et al. (2020). Barillas and Shanken (2017) show that comparing the performance of two factor models f_1 and f_2 (with traded factors) in pricing a set of test assets X is equivalent to comparing the maximum Sharpe ratios that can be obtained with the factors in each model (denoted below as $maxSR^2(f_1)$ vs. $maxSR^2(f_2)$). Indeed, the extent to which model f_1 fails to price assets X and f_2 is given by the extent to which its maximum Sharpe ratio can be increased by including X and f_2 in the investment universe: $maxSR^2(f_1, f_2, X) - maxSR^2(f_1)$. Analogously, the amount of mispricing under the f_2 model is given by $maxSR^2(f_2, f_1, X) - maxSR^2(f_2)$. Therefore, the difference in performance between models f_1 and f_2 is given by the difference $[maxSR^2(f_1, f_2, X) - maxSR^2(f_1)] - [maxSR^2(f_2, f_1, X) - maxSR^2(f_2)] = maxSR^2(f_2) - maxSR^2(f_1)$. Importantly, note that this implies that test assets do not matter if our sole purpose is to compare the two models.

In Table 1 we present these differences in maximum Sharpe ratios between the model specified in the column header minus the model specified in the row header.[10] The column headers specify what variable was used to construct the investment factor (and "None" signifies that no investment factor was used). Panel A uses HXZ-like models and Panel B uses FF5F-style models. The fact that all estimates in the first row in Panel A are negative tells us that all HXZ-style models based on an alternative investment measure (i.e., CAPX, PPE, TOTK, PHK, INTK) perform significantly worse than the original, AG-based, HXZ model when pricing *any* set of test assets.[11] The second row in Panel A of Table 1 suggests that the five alternative HXZ-style models perform significantly better than if they did not contain their investment factor. The third row suggests that they also significantly outperform the FF3F model.[12]

Panel B of Table 1 performs the analogous model-comparison tests, using FF5F-style models instead of HXZ-style models. Again, the first row of Panel B suggests that replacing the AG factor in the FF5F model with a factor based on either of our five investment measures leads to models that significantly underperform FF5F. Strikingly, the statistically insignificant estimates in the second and third row of Panel B suggest that the FF5F-style CAPX, PPE, TOTK, PHK and INTK investment factors can in fact be spanned by the market, size, BM, and profitability factors (second row results) and even by the FF3F factors (third row results). Hence, when constructed using more traditional measures, the investment factor is redundant in the FF5F model.

In Table E6 in the Appendix, we present the performance of these alternative investment models in explaining common anomaly portfolios and bivariate test assets. The results show the same qualitative pattern as the one found in Table 1. Models based on alternative investment measures perform significantly worse than the original, AG-based models. Furthermore, in Section D and Tables E7 and E8 of the Appendix, we show evidence that AG is not a better predictor of future investment, profitability or book-equity growth than CAPX. This casts doubt on the idea that the superior performance of the AG factor (over more traditional investment measures) can be attributable to its being a better proxy for the other key variables in the present value framework and Tobin's Q models (i.e. expected investment, expected profitability and expected book-equity growth).

[10] The p-values in parentheses are calculated using the asymptotics derived in Barillas et al. (2020) (Equations 3 and 4 in their paper).

[11] Note that each of these alternative models differs from the original HXZ model in two respects. First, the AG factor is replaced with a factor based on a different measure of investment. Second, because these HXZ-style factors are based on a 2-by-3-by-3 independent sort on size, profitability and investment, changing the investment measure means the size and profitability factors will also differ between the HXZ model and its alternatives. If we ignored this second effect, the results in the first row of Panel A would be equivalent to saying that the AG factor has a positive alpha when regressed on market, size, profitability and either of the five alternative measures of investment.

[12] Again, ignoring the aforementioned complication arising from the formation of HXZ-style factors, these results are approximately equivalent to saying that the HXZ-style CAPX, PPE, TOTK, PHK, and INTK investment factors can not be spanned by the market, size and profitability factors (second row results) or by the FF3F factors (third row results).

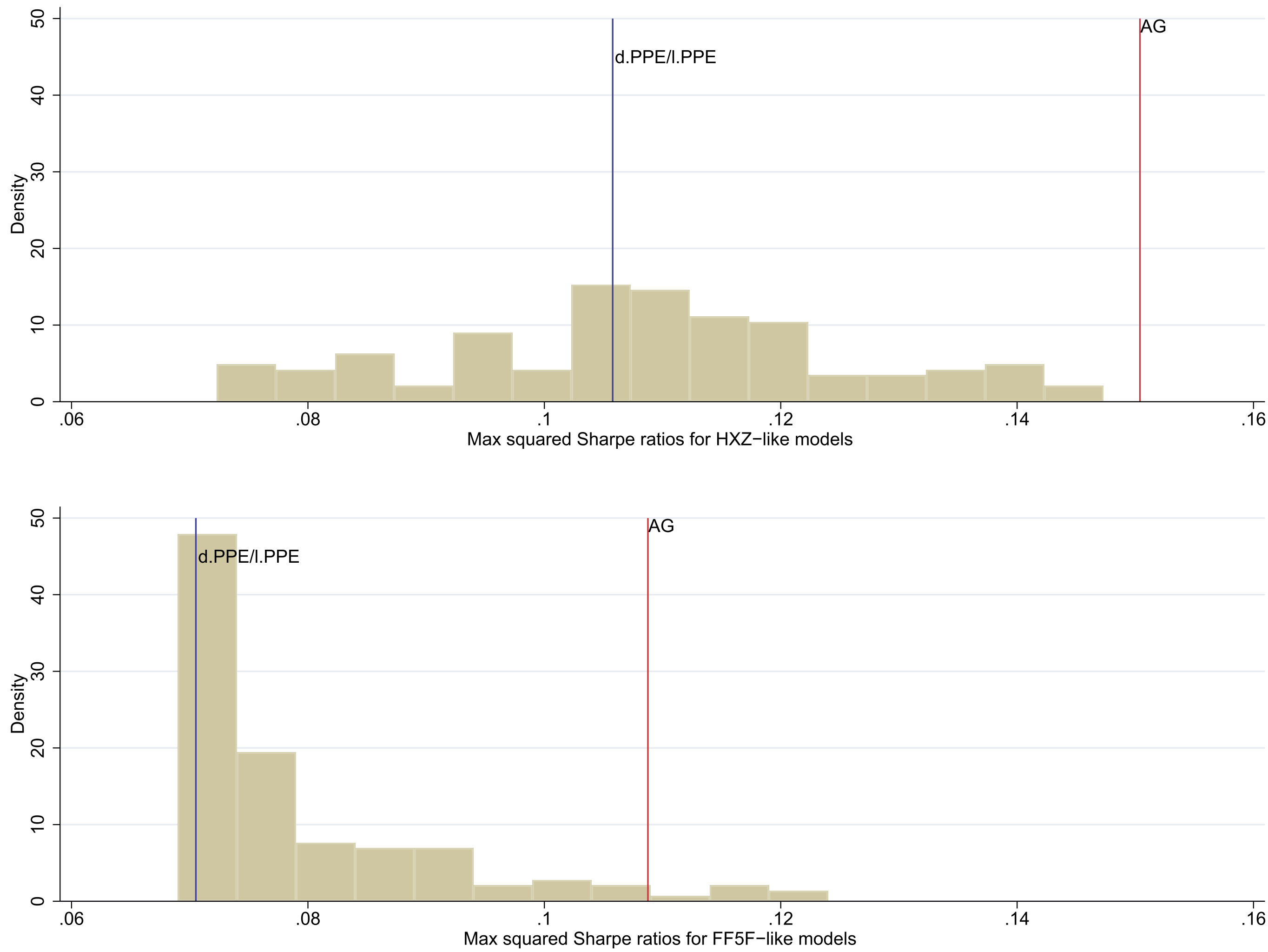

Fig. 1. Performance of HXZ and FF5F using Alternative Investment Factors. *Note*: This figure plots the performance of HXZ-style models (top panel) and FF5F-style models (bottom panel) obtained by replacing the asset-growth-based investment factor in HXZ and FF5F, with a factor based on one of 144 alternative measures of investment. The figures report histograms of maximum squared Sharpe ratios that can be obtained with the factors in each alternative model. As reference points, the red vertical lines show the performance of the original, asset-growth-based HXZ and FF5F models and the blue lines show the performance of the models obtained using the percentage change in PPE to construct the investment factor. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

2.2. A data–mining approach

To verify that the main findings of our analysis are not driven by our particular choice of alternative investment measures, we extend the analysis in the previous section by considering 144 different measures of investment. To construct our set of investment measures we start with three different measures of investment in physical capital (CAPX, change in gross PPE, and CAPX net of PPE sales). We then consider several other investments that the firm could make: change in inventory, change in goodwill, change in capitalized knowledge capital and change in capitalized organizational capital [the latter three measures are calculated as in Peters and Taylor (2017)]. For each of the three choices of physical capital investment, we add every possible combination of the additional four types of investment. This yields $3 \times 2 \times 2 \times 2 \times 2 = 48$ different investment measures. Finally, we use three different lagged normalizing variables [total assets, gross PPE and total capital as measured in Peters and Taylor (2017)], which leads us to $48 \times 3 = 144$ investment variables.

Next, we follow the same approach as in Section 2.1 and we analyze how the performance of the HXZ and FF5F models changes if the asset-growth factor is replaced with a factor based on one of our 144 different measures of investment. Because the purpose of this exercise is strictly to compare model performance, we follow Barillas and Shanken (2017) and restrict our attention to a single key performance measure: the maximum squared Sharpe ratio that can be obtained with the factors in each model.

Fig. 1 shows histograms of these 144 Sharpe ratios from both HXZ-style models (top panel) and FF5F-style models (bottom panel). The vertical lines marked “AG” show the maximum squared Sharpe ratio of the HXZ model (in the top panel) and the FF5F model (in the bottom panel). As a reference point, the lines marked “d.PPE/l.PPE” show the maximum squared Sharpe ratio that can be obtained if we use the percentage change in PPE as our investment measure, rather than AG. The results in Fig. 1 clearly show that the AG-based HXZ and FF5F models are extreme outliers in terms of performance: the HXZ model outperforms every single one of our 144 alternative investment models, and the FF5F model outperforms all but 5 of the 144 models (in unreported results we verify that the difference in performance between these 5 models and AG is not statistically significant).

3. Building factors using subcomponents of asset growth

Our results so far suggest that the investment factor is arguably not driven by traditional measures of investment. Our first step toward ob-

Table 2
Using Sharpe Ratio Tests to Compare HXZ and FF5F to Models Based on Subcomponents of AG.

Panel A1: Comparing HXZ-like models using LHS components of AG

Baseline model	Statistic	None	CASH	INVT	AREC	PPE	INTAN	OTHER
HXZ(AG)	$\Delta(maxSR^2)$	-0.078***	-0.068***	-0.021	-0.018	-0.057***	-0.079***	-0.058***
	p-value	(0.002)	(0.004)	(0.385)	(0.327)	(0.006)	(0.002)	(0.003)
None	$\Delta(maxSR^2)$		0.010	0.057***	0.060***	0.021	-0.000	0.020
	p-value		(0.184)	(0.010)	(0.006)	(0.148)	(0.962)	(0.150)
FF3F	$\Delta(maxSR^2)$	0.026	0.036	0.084***	0.087***	0.048*	0.026	0.047*
	p-value	(0.303)	(0.165)	(0.008)	(0.003)	(0.082)	(0.298)	(0.071)

Panel A2: Comparing FF5F-like models using LHS components of AG

Baseline model	Statistic	None	CASH	INVT	AREC	PPE	INTAN	OTHER
FF5F(AG)	$\Delta(maxSR^2)$	-0.037**	-0.037**	0.000	-0.008	-0.035**	-0.037**	-0.037**
	p-value	(0.037)	(0.049)	(0.996)	(0.597)	(0.031)	(0.032)	(0.024)
None	$\Delta(maxSR^2)$		-0.000	0.037**	0.028*	0.002	-0.001	-0.001
	p-value		(0.919)	(0.032)	(0.072)	(0.731)	(0.473)	(0.671)
FF3F	$\Delta(maxSR^2)$	0.025	0.024	0.062***	0.053**	0.027	0.024	0.024
	p-value	(0.124)	(0.149)	(0.007)	(0.014)	(0.124)	(0.139)	(0.143)

Panel B1: Comparing HXZ-like models using RHS components of AG

Baseline model	Statistic	None	COLIAB	NCOLIAB	DBT	EQ	RE
HXZ(AG)	$\Delta(maxSR^2)$	-0.078***	-0.053***	-0.087***	-0.045*	-0.038*	-0.022
	p-value	(0.002)	(0.004)	(0.001)	(0.065)	(0.060)	(0.339)
None	$\Delta(maxSR^2)$		0.025*	-0.009**	0.033**	0.040**	0.057**
	p-value		(0.065)	(0.034)	(0.026)	(0.014)	(0.012)
FF3F	$\Delta(maxSR^2)$	0.026	0.051**	0.017	0.060**	0.067**	0.083**
	p-value	(0.303)	(0.046)	(0.481)	(0.049)	(0.018)	(0.012)

Panel B2: Comparing FF5F-like models using RHS components of AG

Baseline model	Statistic	None	COLIAB	NCOLIAB	DBT	EQ	RE
FF5F(AG)	$\Delta(maxSR^2)$	-0.037**	-0.039**	-0.039**	0.030	-0.035**	-0.038**
	p-value	(0.037)	(0.024)	(0.021)	(0.223)	(0.025)	(0.026)
None	$\Delta(maxSR^2)$		-0.002***	-0.003	0.067***	0.001	-0.002
	p-value		(0.009)	(0.153)	(0.009)	(0.812)	(0.143)
FF3F	$\Delta(maxSR^2)$	0.025	0.023	0.022	0.091***	0.026	0.023
	p-value	(0.124)	(0.159)	(0.158)	(0.002)	(0.141)	(0.154)

Note: In this table we use maximum Sharpe ratio tests as in Barillas et al. (2020) to compare the performance of the HXZ and FF5F models with that of models based on subcomponents from the left-hand-side (panels A1 and A2) and the right-hand-side (panels B1 and B2) of the balance sheet. On the left-hand side of the balance sheet, we use changes in cash ("CASH"), inventory ("INVT"), accounts receivable ("AREC"), property, plant, and equipment ("PPE"), intangibles ("INTAN"), and other assets ("OTHER", i.e., total assets minus the previous categories). On the right-hand side, we use changes in current operating liabilities ("COLIAB"), non-current operating liabilities ("NCOLIAB"), debt ("DBT"), common equity ("EQ"), and retained earnings ("RE"). In each panel, we report the difference in squared maximum Sharpe ratios between the model specified in the column header and the model specified in the row header. Columns and rows labeled "None" use no investment factor at all. Panels A1 and B1 construct factors as in HXZ and panels A2 and B2 construct factors as in FF5F. p-values are reported in parentheses and are calculated as in Barillas et al. (2020).

taining a better understanding of what may be driving the explanatory power of the AG factor is to investigate what would happen if we constructed the factor using subcomponents of AG rather than AG itself. We decompose a firm's growth in total assets into changes in items from both the left-hand side and the right-hand side of the balance sheet. On the left-hand side, we use changes in cash ("CASH"), inventory ("INVT"), accounts receivable ("AREC"), property, plant, and equipment ("PPE"), intangibles ("INTAN"), and other assets ("OTHER", i.e., total assets minus the previous categories). On the right-hand side, we use changes in current operating liabilities ("COLIAB"), non-current operating liabilities ("NCOLIAB"), debt ("DBT"), common equity ("EQ"), and retained earnings ("RE").[13] All eleven growth measures are normalized by lagged total assets. As a result, the sum of all the subcomponents on each side of the balance sheet amounts to the firm's percentage growth in total assets.

In Table 2, we perform formal model comparison tests based on the maximum squared Sharpe ratio measure detailed in Barillas and Shanken (2017) and Barillas et al. (2020). These tests are analogous to the ones presented in Table 1, the difference being that in Table 2 we compare the HXZ and FF5F models with their counterparts using subcomponents of AG to form the investment factor. In Panels A1 and B1, we compare HXZ-style models and in Panels A2 and B2 we compare FF5F-style models. In Panels A1 and A2, we create factors based on the decomposition of AG into its subcomponents from the left-hand-side of the balance sheet, and in Panels B1 and B2 we use subcomponents from the right-hand-side of the balance sheet. Each estimate in the table represents the difference in maximum squared Sharpe ratio that can be obtained using the factors of the model in the column header minus the analogous figure for the model in the row header. For example, the −0.068 estimate in the "CASH" column in Panel A1 tells us that the maximum squared Sharpe ratio we can obtain using the factors in the HXZ model where the investment factor is built using growth in cash

[13] Current operating liabilities are current liabilities minus long-term debt due within a year. Noncurrent liabilities are total liabilities minus current liabilities minus long-term debt. Debt is calculated as long-term debt plus debt due within a year plus preferred stock. Common equity is total assets minus total liabilities minus preferred stock minus retained earnings.

holdings is 0.068 lower than the maximum squared Sharpe ratio that can be obtained with the factors in the original HXZ model.

One of the main findings in Panel A1 of Table 2 is in the first row, columns "INVT" and "AREC". The fact that those estimates are statistically insignificant tells us that, if we build the HXZ model using either the inventory component (INVT) of AG, or the accounts receivable (AREC) component, we obtain models that do not perform significantly differently from HXZ, regardless of the test assets we use. In contrast, the "PPE" and "INTAN" columns show (in the first row) that when the HXZ model is built using measures of investment in long-term assets, be they physical (PPE) or intangible (INTAN), we obtain models that perform significantly worse than the original HXZ model. In fact, the second row in Panel A1 shows that, if we build the investment factor using subcomponents other than inventory or accounts receivable, we obtain models that perform no better than if we had no investment factor at all. Panel A2 show that the exact same conclusions apply when we compare FF5F-style models. Table E9 in the Appendix shows how all these alternative models perform when explaining common anomaly portfolios and bivariate-sort test assets. The same general conclusions apply. The performance of models based on inventory and accounts receivable is close to the original HXZ and FF5F models, while the models based on all the other left-hand-side subcomponents perform significantly worse.

Comparing the performance of models based on right-hand-side subcomponents of AG yields a less unified picture between HXZ- and FF5F-style models. This is the main reason why, going forward, we will focus mostly on the left-hand-side decomposition. The first row in Panel B1 shows that when we build the HXZ model using retained earnings (RE) for the investment factor, we obtain a model that does not perform significantly worse than HXZ. The same can not be said about the other four subcomponents. Panel B2 shows that if we were to build the FF5F model using changes in debt, we do not lose performance with respect to the original model, but performance does deteriorate significantly when using any of the other four subcomponents.

3.1. Inventory and accounts receivable factors span the asset growth factor

The results in Table 2 show that the performance of the HXZ and FF5F models does not drop significantly if their "investment" factor is constructed using inventory-growth (INVT) or accounts-receivable growth (AREC) instead of AG. In this section, we show that the pricing information that the AG factor contributes to the HXZ and FF5F models, is in fact spanned by the INVT and AREC factors (but not by the other subcomponents of AG).

We begin by running spanning regressions of the form:

$$R_{AG,t} = \alpha + \beta_{INVT} R_{INVT,t} + \beta_{AREC} R_{AREC,t} + \gamma X_t + \epsilon_t \quad (1)$$

where $R_{AG,t}$, $R_{INVT,t}$, and $R_{AREC,t}$ represent the returns on the AG, INVT, and AREC factors, respectively, and the X_t term encompasses the returns on all remaining factors in the HXZ model (as presented in Panel A of Table 3) or the FF5F model (as presented in Panel B of Table 3). It is important to control for these additional factors as our investigation is focused on the pricing power of the AG factor within the context of the HXZ and FF5F models, rather than its performance in isolation. Therefore, it is essential to take into account the correlation of the AG factor with the other existing factors in those models.

The results obtained from estimating Equation (1) are presented in the first column of Table 3. The alpha coefficients are statistically insignificant in both panels, which suggests that the pricing information that the AG factor contributes to the HXZ and FF5F models is captured by the joint presence of INVT and AREC factors. In Table E10 in the Appendix, we run similar spanning regressions to test if the AG factor is spanned by any one of its individual subcomponents and we find that this is not the case. Hence, the INVT and AREC factors are *both* needed to span the AG factor. In the remaining columns of Table 3, we use different subcomponents of AG (from the left-hand side of the balance sheet) as the dependent variable in Equation (1). The alphas continue to remain insignificant in all of these specifications, which indicates that the INVT and AREC factors (used together) also capture the pricing information of all other AG subcomponent factors.

Table 3
Spanning Regressions of AG factor and Subcomponents on Inventory and Accounts Receivable Factors.

Dependent Variable:	R_{AG}	R_{CASH}	R_{PPE}	R_{INTAN}	R_{OTHER}
Panel A: HXZ-Style Models					
α	0.001	-0.000	0.001	-0.000	0.000
	(1.64)	(-0.11)	(1.29)	(-0.36)	(0.86)
R_{MKT}	-0.026*	-0.021	-0.003	0.025	-0.017
	(-1.88)	(-1.51)	(-0.15)	(1.44)	(-1.21)
R_{ME}	0.075**	0.074***	0.105***	0.086***	0.011
	(2.49)	(3.27)	(3.50)	(3.48)	(0.34)
R_{ROE}	0.034	0.013	0.055	0.050	0.035
	(0.79)	(0.52)	(1.50)	(1.22)	(0.84)
R_{INVT}	0.310***	-0.042	0.171**	0.013	0.012
	(6.23)	(-0.82)	(2.57)	(0.23)	(0.26)
R_{AREC}	0.631***	0.280***	0.262***	0.177***	0.338***
	(8.95)	(5.93)	(5.80)	(3.09)	(6.53)
Obs	564	564	564	564	564
R^2	0.648	0.197	0.192	0.109	0.292
Panel B: FF5F-Style Models					
α	0.001	-0.000	0.000	-0.000	-0.000
	(1.27)	(-1.10)	(0.43)	(-0.53)	(-0.61)
R_{MKT}	-0.024	-0.016	0.024	0.045***	-0.008
	(-1.36)	(-0.84)	(1.22)	(3.48)	(-0.57)
R_{ME}	0.063***	0.062**	0.071**	0.095***	0.031
	(3.94)	(2.32)	(2.39)	(3.71)	(1.60)
R_{BM}	0.205***	0.119***	0.256***	0.061**	0.129***
	(8.13)	(5.19)	(6.12)	(2.09)	(3.81)
R_{PROF}	-0.012	0.017	0.025	0.136***	0.085***
	(-0.42)	(0.40)	(0.65)	(3.41)	(2.79)
R_{INVT}	0.323***	-0.042	0.265***	0.010	0.006
	(8.76)	(-1.01)	(2.88)	(0.15)	(0.14)
R_{AREC}	0.472***	0.131***	-0.032	0.118***	0.220***
	(9.17)	(2.96)	(-0.38)	(2.68)	(3.85)
Obs	564	564	564	564	564
R^2	0.740	0.236	0.320	0.183	0.331

Note: This table presents estimates from regressing the returns of the AG, CASH, PPE, INTANT, and OTHER factors, on the returns of the INVT and AREC factors, and the remaining factors in the HXZ model (Panel A) or the FF5F model (Panel B). See Equation (1) for details. All regressions use monthly data from 1972 to 2018. Standard errors are corrected for heteroskedasticity and autocorrelation using the Newey and West (1987) procedure with up to 12 lags. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

We next test whether the INVT and AREC factors are spanned by any of the subcomponents of AG. Specifically, in Table 4, we run regressions of the following form:

$$R_{INVT,t} = \alpha + \beta_{SUB} R_{SUB,t} + \gamma X_t + \epsilon_t \quad (2)$$

where each column in the table uses a different subcomponent of AG (SUB) from the left-hand-side of the balance sheet (i.e., CASH, AREC, PPE, INTAN, or OTHER) as the main explanatory variable. To control for the possibility that some information may be lost by splitting the individual subcomponents of AG, we also construct a factor using growth in all assets but inventory (we call this the $AG - INVT$ factor). Once again, Panel A reports results using HXZ–style factors and Panel B reports results using FF5F–style factors and the X_t term contains all the remaining factors in the HXZ model (in Panel A) or the FF5F factor (in Panel B).

The results in Table 4 indicate that the alpha coefficients are statistically significant in all specifications, which supports the conclusion that the INVT factor is not spanned by any of the other individual subcomponent of AG, or by all of them summed up into the $AG - INVT$ factor (last column in the table). In Table 5, we use returns on the AREC factor

Table 4
Spanning Regressions of the Inventory Factor on AG Subcomponents.

Main RHS Factor:	R_{INVT}	R_{INVT}	R_{INVT}	R_{INVT}	R_{INVT}	R_{INVT}
Panel A: HXZ-Style Models						
α	0.003***	0.002**	0.003***	0.003***	0.003***	0.002**
	(4.55)	(2.37)	(3.68)	(4.93)	(4.01)	(2.42)
R_{MKT}	-0.087***	-0.029	-0.079***	-0.099***	-0.074***	-0.044**
	(-3.91)	(-1.60)	(-3.75)	(-4.62)	(-3.57)	(-2.19)
R_{ME}	-0.095***	-0.051**	-0.112***	-0.100***	-0.084***	-0.105***
	(-2.87)	(-1.98)	(-3.40)	(-3.29)	(-2.69)	(-3.53)
R_{ROE}	0.010	0.039	0.004	-0.001	0.007	0.028
	(0.19)	(1.04)	(0.09)	(-0.02)	(0.16)	(0.67)
R_{CASH}	0.206**					
	(2.31)					
R_{AREC}		0.487***				
		(8.52)				
R_{PPE}			0.333***			
			(4.47)			
R_{INTAN}				0.203**		
				(2.04)		
R_{OTHER}					0.356***	
					(5.07)	
$R_{AG-INVT}$						0.423***
						(7.13)
Obs	564	564	564	564	564	564
R^2	0.137	0.353	0.208	0.136	0.180	0.304
Panel B: FF5F-Style Models						
α	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(4.33)	(3.62)	(4.04)	(4.37)	(4.27)	(3.67)
R_{MKT}	-0.059***	-0.037**	-0.060***	-0.061***	-0.056***	-0.043**
	(-3.20)	(-2.15)	(-3.30)	(-3.13)	(-2.91)	(-2.23)
R_{ME}	-0.160***	-0.149***	-0.168***	-0.168***	-0.163***	-0.173***
	(-4.74)	(-4.57)	(-4.97)	(-5.19)	(-4.84)	(-5.44)
R_{BM}	0.241***	0.182***	0.176***	0.231***	0.220***	0.139***
	(7.83)	(4.54)	(4.90)	(7.17)	(6.19)	(3.22)
R_{PROF}	-0.215***	-0.163***	-0.211***	-0.223***	-0.219***	-0.184***
	(-4.53)	(-3.59)	(-4.51)	(-5.47)	(-4.81)	(-4.14)
R_{CASH}	-0.019					
	(-0.27)					
R_{AREC}		0.232***				
		(2.97)				
R_{PPE}			0.199***			
			(2.99)			
R_{INTAN}				0.077		
				(0.68)		
R_{OTHER}					0.099	
					(1.35)	
$R_{AG-INVT}$						0.245***
						(3.23)
Obs	564	564	564	564	564	564
R^2	0.360	0.396	0.393	0.362	0.364	0.397

Note: This table presents estimates from regressing the returns of the INVT factor, on the returns of each of the subcomponents of AG (CASH, INVT, AREC, PPE, INTAN, and OTHER), and the remaining factors in the HXZ model (Panel A) or the FF5F model (Panel B). In the last column of the table, we use as explanatory variable a factor constructed based on growth in all assets but inventory (i.e., using $AG - INVT$ as the sorting variable). All regressions use monthly data from 1972 to 2018. Standard errors are corrected for heteroskedasticity and autocorrelation using the Newey and West (1987) procedure with up to 12 lags. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

as the dependent variable in Equation (2) and perform tests analogous to the ones in Table 4. We find that the AREC also can not be spanned by any other subcomponent of AG, introduced either individually or as a sum (i.e. the $AG - AREC$ factor in the last column).[14]

We believe that, taken together, the results in this section show convincingly that the INVT and AREC factors (together, but not separately) contain the lion's share of the pricing information that the AG factor contributes to the HXZ and FF5F models. Not only do the INVT and AREC factors span the returns of the AG factor, but they themselves

[14] Table E11 in the Appendix shows that the AG, INVT, and AREC factors are also not spanned by the other subcomponents of AG (CASH, PPE, INTAN, and OTHER) when all those subcomponent factors are introduced as explanatory variables in our spanning regressions *at the same time*. Specifically, all alpha estimates in regressions of the form $R_{F,t} = \alpha + \beta_{CASH} R_{CASH,t} + \beta_{PPE} R_{PPE,t} + \beta_{INTAN} R_{INTAN,t} + \beta_{OTHER} R_{OTHER,t} + \gamma X_t + \epsilon_t$ are statistically significant, whether the dependent variable factor F is AG, INVT, or AREC.

Table 5
Spanning Regressions of the Accounts Receivable Factor on AG Subcomponents.

Main RHS Factor:	R_{AREC}	R_{AREC}	R_{AREC}	R_{AREC}	R_{AREC}	R_{AREC}
Panel A: HXZ-Style Models						
α	0.003***	0.002**	0.003***	0.003***	0.002***	0.001**
	(4.46)	(2.36)	(3.84)	(4.63)	(4.29)	(2.44)
R_{MKT}	-0.109***	-0.086***	-0.116***	-0.141***	-0.093***	-0.061***
	(-4.87)	(-3.85)	(-4.76)	(-5.96)	(-4.34)	(-2.81)
R_{ME}	-0.091***	-0.006	-0.096***	-0.093***	-0.058**	-0.076***
	(-2.90)	(-0.21)	(-3.43)	(-3.08)	(-2.06)	(-2.91)
R_{ROE}	-0.018	-0.009	-0.029	-0.041	-0.029	-0.016
	(-0.32)	(-0.17)	(-0.48)	(-0.71)	(-0.73)	(-0.43)
R_{CASH}	0.557***					
	(8.24)					
R_{INVT}		0.546***				
		(9.44)				
R_{PPE}			0.413***			
			(6.49)			
R_{INTAN}				0.398***		
				(3.91)		
R_{OTHER}					0.692***	
					(13.00)	
$R_{AG-AREC}$						0.615***
						(13.14)
Obs	564	564	564	564	564	564
R^2	0.270	0.371	0.266	0.208	0.348	0.464
Panel B: FF5F-Style Models						
α	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(4.29)	(3.00)	(3.99)	(4.09)	(4.49)	(3.49)
R_{MKT}	-0.085***	-0.076***	-0.091***	-0.098***	-0.080***	-0.071***
	(-5.10)	(-3.80)	(-5.17)	(-5.75)	(-4.62)	(-3.91)
R_{ME}	-0.068***	-0.015	-0.055**	-0.075***	-0.063***	-0.056**
	(-3.30)	(-0.67)	(-2.43)	(-3.53)	(-2.65)	(-2.42)
R_{BM}	0.208***	0.184***	0.233***	0.220***	0.175***	0.112***
	(7.50)	(5.52)	(8.17)	(7.03)	(5.05)	(2.71)
R_{PROF}	-0.224***	-0.173***	-0.225***	-0.250***	-0.238***	-0.194***
	(-5.55)	(-4.05)	(-5.23)	(-5.89)	(-6.47)	(-4.93)
R_{CASH}	0.229***					
	(3.25)					
R_{INVT}		0.240***				
		(3.20)				
R_{PPE}			0.025			
			(0.37)			
R_{INTAN}				0.228***		
				(2.79)		
R_{OTHER}					0.361***	
					(3.73)	
$R_{AG-AREC}$						0.302***
						(3.53)
Obs	564	564	564	564	564	564
R^2	0.370	0.387	0.352	0.370	0.404	0.403

Note: This table presents estimates from regressing the returns of the AREC factor, on the returns of each of the subcomponents of AG (CASH, INVT, AREC, PPE, INTAN, and OTHER), and the remaining factors in the HXZ model (Panel A) or the FF5F model (Panel B). In the last column of the table, we use as explanatory variable a factor constructed based on growth in all assets but accounts receivable (i.e., using $AG - AREC$ as the sorting variable). All regressions use monthly data from 1972 to 2018. Standard errors are corrected for heteroskedasticity and autocorrelation using the Newey and West (1987) procedure with up to 12 lags. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

are not spanned by any other subcomponent of AG (either introduced individually or as a group).

4. Asset growth and macroeconomic factors

The fact that the AG-based HXZ and FF5F models perform so well in describing the cross-section of stock returns suggests that the AG factor does a good job of capturing some macroeconomic source of comovement that, given the results in the prior three sections, (i) is not captured by other measures of investment (e.g., PPE growth), but (ii) is captured by the factors based on inventory growth (INVT) and accounts-receivable growth (AREC). Hence, one approach to gaining a deeper understanding of the economic mechanisms responsible for the superior performance of the AG factor, is to look at which macroeconomic shocks are significant drivers for AG–, INVT– and AREC–sorted portfolio returns, but *not* for returns of PPE-sorted portfolios.[15]

[15] To keep the size and number of tables manageable, we chose PPE (growth) as a representative member of all the alternative measures of investment we

The literature studying macroeconomic shocks that can generate cross-sectional risk dispersion is vast, and we do not claim to have fully covered it in our tests below. Nevertheless, we believe we have put together a representative list of variables that could be driving the comovement captured by the AG variable. Specifically, as detailed in the list below, we use macroeconomic measures of shocks to productivity, consumption, liquidity, uncertainty, financing costs, production networks, and market sentiment:

1. TFP is the measure of utilization-adjusted TFP shocks from Fernald (2012).
2. IST is the investment-specific technology factor from Papanikolaou (2011).[16]
3. RD is an innovation factor based on Elsaify (2017).[17]
4. CAY is the consumption-wealth ratio from Lettau and Ludvigson (2001).
5. LIQ is the aggregate liquidity factor of Pastor and Stambaugh (2003).
6. UNC is the macroeconomic uncertainty factor of Jurado et al. (2015).
7. ICS is the measure of aggregate equity financing shocks from Belo et al. (2019).
8. LEV is the financial intermediary leverage factor of Adrien et al. (2014).
9. CRAT is the financial intermediary capital ratio factor of He et al. (2017).
10. RS: is the production network risk factor of Grigoris et al. (2023).[18]
11. BW is the equity–market sentiment measure from Baker and Wurgler (2006).
12. HYS is the "high-yield share" measure used to proxy for credit–market sentiment in Greenwood and Hanson (2013).[19]

The ICS factor comes at an annual frequency, the TFP, CAY, LEV, and HYS factors come at a quarterly frequency, and the rest of the factors have a monthly frequency. For CAY, UNC, BW, and HYS, we use AR(1) residuals instead of levels (to approximate the unexpected component of the factors). The remaining factors are either return spreads (RD, IST, and RS) or are constructed as innovations to begin with (TFP, LIQ, ICS, LEV, CRAT).

For each macroeconomic factor ($MACRO$) from the list above, we hypothesize a stochastic discount factor (M) of the form:

$$M_t = 1 - b_{MKT} MKT_t - b_{MACRO} MACRO_t, \tag{3}$$

where MKT is the (demeaned) excess return on the value-weighted market portfolio, and the time period t has the same frequency as the $MACRO$ factor (i.e., for annual and quarterly factors, MKT_t stands for the cumulative returns on the market portfolio in period t). The $MACRO_t$ factor is also demeaned (after extracting the AR(1) residual, when appropriate, as explained above). It is important to note that the factor loadings b_{MKT} and b_{MACRO} are not the risk premia on the MKT and $MACRO$ factors, but a transformation of these premia that takes into account the correlation between the factors. As explained in Cochrane (2005), pages 260-261, each factor's SDF loading measures the extent to which that factor contains information (relevant for pricing the test assets) that is not already captured by the other factors in the SDF.

As test assets, we use four different groups of portfolios sorted on profitability and either AG, INVT, AREC, or PPE growth. As explained for example in Kogan and Papanikolaou (2012), investment-based models predict a negative relation between investment and discount rates only when we control for profitability. Since we are interested in testing whether the AG, INVT, AREC, and PPE factors are in fact capturing this investment-risk relation, controlling for profitability is essential.[20] We measure profitability using the same variable used to construct the FF5F profitability factor (to match the annual frequency of the AG variable and its subcomponents), and we use NYSE cutoffs to form the portfolios (to be consistent with the methodology used to construct factors and anomalies in the rest of our paper).

In Table 6, we estimate the factor loadings b_{MKT} and b_{MACRO} by first-stage GMM, using the identity matrix to weigh moment restrictions. We use the standard moment conditions $\mathbb{E}[M_t r^e_{i,t}] = 0$, where $r^e_{i,t}$ represents the excess returns on a test asset i. Each column in the table corresponds to a different model (i.e., a different choice of $MACRO$ factor in Equation (3)), and each panel uses a different set of test assets to estimate each model. Specifically, each panel prices 25 portfolios constructed with 5 by 5 bivariate sorts of profitability by AG (Panel A), INVT (Panel B), AREC (Panel C), or PPE growth (Panel D). As measures of fit, we report the sum of squared (pricing) errors (SSQE) implied from each model, as well as the mean absolute pricing errors (MAPE).[21] As a point of reference, in the first column of each panel, we also report results using the CAPM (i.e., no $MACRO$ factor in Equation (3)).

One of the key findings in Table 6 is that almost all macro factors have significant pricing power in the cross-section of AG-based assets (Panel A), the only exception being the liquidity (LIQ) and credit-market sentiment (HYS) factors. This helps to at least partially explain why the AG-based HXZ and FF5F models do such a great job in describing the cross-section of stock returns. More importantly though, since our paper focuses on the *difference* in performance between factor models using traditional investment measures like PPE growth, and models using AG, INVT, and AREC, the key insights for our paper come from analyzing how the results in panels A, B, and C are similar to each other, and how they are different from the results in Panel D.

From this point of view, Table 6 conveys two main findings. First, while the technology-shock factors (TFP, IST, and RD) are significant across the AG, INVT, and AREC cross-sections (except TFP in Panel B), they are also significant in the cross-section of PPE portfolios. This suggests that the inferior performance of the PPE-based factor models is unlikely to be caused by its lower ability to capture macro technology shocks (i.e., the kind of shocks employed in production-based models like Tobin's Q or extensions thereof). Second, as a group, the AG, INVT, and AREC portfolios seem to capture financing-related macro shocks (ICS, LEV, CRAT, BW) better than the PPE portfolios.

The CAY, UNC, and RS factors are also significant in the cross-section of AG portfolios. However, we do not believe they are responsible for the superior performance of AG-based models, for two main reasons. First, the RS factor is also significant in the cross-section of PPE portfolios. Second, as we showed in Section 3.1, the INVT and AREC factors (together) should account for all the pricing power of the AG factor within the HXZ and FF5F models. However, Table 6 shows that the CAY and UNC factors are *not* significant in either Panels B or C.

employed in the prior three sections. All results in this section are qualitatively unchanged if we use one of those alternative measures instead of PPE.

[16] Specifically, we use the measure based on the return spread between investment- and consumption-good producing firms.

[17] This is calculated as the spread between the value-weighted returns of firms in the top decile and bottom decile of R&D intensity. Following Elsaify (2017), R&D intensity is calculated as R&D divided by CAPX plus R&D.

[18] This is calculated as the return spread between firms with high (top decile) receivables-to-sales ratios and with low (bottom decile) receivables-to-sales ratios.

[19] This measure is calculated as the aggregate share of high-yield bonds as a percentage of the total dollar amount of new bond issuance in a given quarter.

[20] Nevertheless, we find that our results are qualitatively similar if the test assets are single-sorted portfolios based on AG, INVT, AREC, and PPE growth. See Table E12 in the Appendix for details.

[21] Both measures of fit have been annualized so they can be compared across models (columns) with different frequencies. When estimating each model, the returns of the test assets and the market portfolio are compounded to match the frequency of the $MACRO$ factor included in the SDF.

Table 6
Pricing Double Sorted VW Portfolios using Macroeconomic Variables.

Panel A: Risk premia using VW returns on 25 AG–PROF portfolios

	CAPM	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	BW	HYS
b_{MACRO}		-0.16*	-9.13***	-3.92**	124.24**	15.92	-52.61*	0.08*	0.14**	11.35*	-18.54***	6.75***	4.23
		(-1.69)	(-3.70)	(-2.10)	(2.16)	(1.57)	(-1.83)	(1.95)	(2.07)	(1.94)	(-3.02)	(2.68)	(1.13)
b_{MKT}	2.79**	2.80***	6.55***	5.67***	5.86***	-3.27	-0.87	1.99	1.83	-9.37	9.49***	4.16**	1.35
	(2.52)	(2.69)	(4.31)	(3.43)	(2.85)	(-0.72)	(-0.48)	(1.54)	(1.14)	(-1.44)	(3.63)	(2.04)	(0.76)
SSQE	1.95	1.87	0.86	0.75	1.46	1.44	1.56	1.82	1.20	1.53	1.09	0.70	3.01
MAPE	2.12	2.00	1.37	1.38	1.95	1.83	1.79	2.03	1.80	1.89	1.48	1.30	2.68

Panel B: Risk premia using VW returns on 25 INVT–PROF portfolios

	CAPM	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	BW	HYS
b_{MACRO}		-0.08	-7.73***	-3.38**	-7.47	4.18	10.92	0.04	0.00	3.94	-9.63**	4.76***	5.11
		(-0.96)	(-2.77)	(-2.07)	(-0.23)	(0.87)	(0.93)	(1.18)	(0.15)	(1.05)	(-2.43)	(2.67)	(1.62)
b_{MKT}	2.57**	2.39**	5.90***	5.18***	1.99*	0.94	3.32***	2.00*	2.22**	-1.55	6.38***	3.74**	0.86
	(2.32)	(2.41)	(3.47)	(3.26)	(1.69)	(0.40)	(2.80)	(1.95)	(2.35)	(-0.36)	(3.42)	(2.19)	(0.50)
SSQE	1.87	1.90	1.16	0.99	1.93	1.84	1.86	2.01	1.99	1.85	1.92	1.36	2.84
MAPE	1.97	1.99	1.69	1.57	2.03	1.88	1.92	2.06	2.12	2.04	2.12	1.77	2.72

Panel C: Risk premia using VW returns on 25 AREC–PROF portfolios

	CAPM	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	BW	HYS
b_{MACRO}		-0.18*	-8.35***	-3.22*	5.94	7.35	-39.16	0.01	0.07	11.34*	-13.76***	4.82***	-0.70
		(-1.66)	(-3.07)	(-1.88)	(0.23)	(1.34)	(-1.38)	(0.53)	(1.53)	(1.95)	(-3.44)	(2.86)	(-0.30)
b_{MKT}	2.64**	2.75**	6.17***	5.07***	2.43**	-0.21	-0.06	2.18**	2.03*	-9.44	7.84***	3.81**	2.96**
	(2.39)	(2.50)	(3.78)	(3.09)	(1.97)	(-0.08)	(-0.04)	(2.36)	(1.74)	(-1.48)	(3.96)	(2.11)	(2.27)
SSQE	1.63	1.48	0.61	0.74	1.64	1.52	1.45	1.80	1.51	1.26	1.19	0.85	2.90
MAPE	1.96	1.89	1.29	1.41	1.95	1.92	1.84	2.06	1.86	1.87	1.69	1.53	2.73

Panel D: Risk premia using VW returns on 25 PPE–PROF portfolios

	CAPM	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	BW	HYS
b_{MACRO}		-0.15*	-6.45**	-2.78*	45.57	10.86**	-5.34	0.02	0.06	5.40	-13.29**	2.19	2.70
		(-1.93)	(-2.19)	(-1.74)	(1.46)	(2.10)	(-0.34)	(0.62)	(1.38)	(1.19)	(-2.03)	(1.64)	(1.01)
b_{MKT}	2.69**	2.67**	5.38***	4.76***	3.56***	-1.61	2.31	2.18**	2.08*	-3.01	7.66***	3.19**	1.72
	(2.39)	(2.50)	(3.14)	(3.04)	(2.77)	(-0.59)	(1.58)	(2.33)	(1.78)	(-0.59)	(2.96)	(2.43)	(1.26)
SSQE	1.13	1.03	0.71	0.69	1.08	0.66	1.12	1.22	1.05	1.06	1.10	1.05	2.07
MAPE	1.57	1.51	1.12	1.18	1.65	1.29	1.55	1.62	1.57	1.44	1.49	1.47	2.16

Note: This table presents GMM estimates of the SDF factor loadings and pricing errors from asset pricing models (Equation (3)) in which the SDF is a linear combination of the market factor (MKT) and an additional macroeconomic shock ($MACRO$). Each column in the table corresponds to a different model (i.e., different choice of $MACRO$) from the following list: (1) TFP: utilization-adjusted total factor productivity shocks [Fernald (2012)], (2) IST: investment-specific technology shocks [Papanikolaou (2011)], which we estimate as the return spread between investment- and consumption-good producing firms, (3) CAY: consumption-wealth ratio [Lettau and Ludvigson (2001)], (4) LIQ: aggregate liquidity [Pastor and Stambaugh (2003)], (5) UNC: macroeconomic uncertainty shocks [Jurado et al. (2015)], (6) ICS: aggregate equity financing shocks [Belo et al. (2019)], (7) LEV: financial intermediary leverage factor [Adrien et al. (2014)], (8) CRAT: financial intermediary capital ratio factor [He et al. (2017)], (9) RS: production network risk factor [Grigoris et al. (2023)], which we estimate as the return spread between firms with high vs low receivables-to-sales ratios, (10) BW: equity market sentiment [Baker and Wurgler (2006)], (11) HYS: credit market sentiment, which we measure using the aggregate share of high-yield new bond issuances as in Greenwood and Hanson (2013). Each panel uses a different set of test assets to estimate each model. We use 25 test assets in each panel, constructed using 5 by 5 bivariate (independent) sorts on profitability and one of AG, INVT, AREC, and PPE respectively. We use NYSE quintile cutoffs to form the test asset portfolios. As measures of fit, we report the sum of squared (pricing) errors (SSQE) implied from each model, as well as the mean absolute pricing errors (MAPE). These measures of fit have been annualized, so they are comparable across models. As a point of reference, we also report results using the CAPM (i.e., no macro factor $MACRO$ in Equation (3)) in the first column of each panel. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Overall, the results in Table 6 suggest that the superior performance of the AG, INVT, and AREC factors over traditional investment factors is likely related to their ability to capture aggregate financing shocks, not productivity/technology shocks. Digging a bit deeper, the only factor that significantly helps price the AG, INVT, and AREC assets but *not* the PPE assets is the equity-market sentiment (BW) factor. As such, we go one step further, and test if this factor captures independent pricing information not already contained in the other macroeconomic factors used in our tests. To this end, we build three-factor SDFs of the form:

$$M_t = 1 - b_{MKT} MKT_t - b_{BW} BW_t - b_{MACRO} MACRO_t, \tag{4}$$

where $MACRO_t$ is one of the factors used in our prior tests. We then repeat the tests in Table 6 using the same moment restrictions $\mathbb{E}[M_t r^e_{i,t}] = 0$ applied to the same four groups of 25 test assets.

The results are reported in Table 7. The key takeaway from this table is that, in almost all models (columns), the BW factor loading remains significant when pricing AG, INVT, and AREC portfolios (Panels A, B, and C), and insignificant when pricing PPE portfolios (Panel D). The one exception is in Panels A and C, when the $MACRO$ factor in the SDF is the equity-issuance cost (ICS) factor of Belo et al. (2019). This result is perhaps not surprising since, as Belo et al. (2019) point out, the ICS factor should capture all drivers of equity issuance costs, including equity market sentiment. Table 7 also shows that the BW factor drives out the pricing power of almost all other factors for AG, INVT, and AREC portfolios (with the lone exceptions being ICS in Panel A, IST, RD, and RS in Panel B, and IST and RS in Panel C). Importantly for our study, this is not the case for PPE portfolios (Panel D), where the TFP, IST, RD, CAY, LIQ, and RS factors are still significant.

5. Investigating the economic mechanism

Our main result, that the superior performance of the AG, INVT, and AREC factors seems to be driven by aggregate financing shocks, can in principle be rationalized by models as in Belo et al. (2019) and

Table 7
Pricing Double Sorted VW Portfolios using Macroeconomic Variables: Three Factor Models.

Panel A: Risk premia using VW returns on 25 AG–PROF portfolios

	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	HYS
b_{BW}	13.27**	4.58**	4.13**	11.75**	5.98***	6.56***	-0.97	10.24*	6.85***	3.96**	10.99*
	(2.00)	(2.04)	(2.00)	(1.97)	(3.06)	(2.93)	(-0.17)	(1.91)	(2.75)	(1.99)	(1.85)
b_{MACRO}	-0.06	-4.35	-2.15	69.90	7.21	-4.80	0.08*	0.08	-0.13	-11.34	-2.99
	(-0.42)	(-1.12)	(-1.10)	(1.16)	(0.93)	(-0.21)	(1.84)	(1.17)	(-0.03)	(-1.50)	(-1.00)
b_{MKT}	2.29	5.52***	5.22***	4.12*	1.26	3.79*	2.02	1.86	4.41	8.22***	4.17*
	(1.27)	(2.75)	(2.66)	(1.76)	(0.36)	(1.67)	(1.63)	(0.98)	(0.87)	(2.98)	(1.94)
SSQE	0.87	0.58	0.52	0.73	0.61	0.69	1.82	0.72	0.70	0.85	1.66
MAPE	1.53	1.10	1.15	1.36	1.12	1.28	2.05	1.38	1.30	1.30	1.96

Panel B: Risk premia using VW returns on 25 INVT–PROF portfolios

	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	HYS
b_{BW}	10.63**	2.82*	2.73**	10.14***	4.72***	4.86***	8.48***	10.92**	4.94***	5.01**	8.42***
	(2.44)	(1.73)	(2.02)	(2.68)	(2.61)	(2.74)	(3.17)	(2.51)	(2.69)	(2.48)	(2.95)
b_{MACRO}	0.08	-6.02*	-2.81*	10.62	3.25	16.25	-0.01	-0.05	-1.44	-10.32*	2.57
	(0.95)	(-1.90)	(-1.69)	(0.26)	(0.64)	(0.96)	(-0.20)	(-0.99)	(-0.31)	(-1.81)	(0.90)
b_{MKT}	1.97	5.85***	5.41***	2.48	2.46	4.89**	1.85*	2.43	5.42	8.21***	2.11
	(1.24)	(3.12)	(3.01)	(1.59)	(0.87)	(2.56)	(1.92)	(1.56)	(1.00)	(2.97)	(1.10)
SSQE	0.96	1.01	0.85	0.98	1.35	1.33	1.82	0.92	1.35	1.25	1.78
MAPE	1.62	1.55	1.45	1.59	1.67	1.70	1.94	1.52	1.75	1.79	2.23

Panel C: Risk premia using VW returns on 25 AREC–PROF portfolios

	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	HYS
b_{BW}	7.44**	2.31*	2.55*	7.94**	4.71***	4.76***	0.43	7.58**	4.44***	3.27**	7.50**
	(2.52)	(1.69)	(1.80)	(2.40)	(2.66)	(2.95)	(0.10)	(2.44)	(2.64)	(2.42)	(2.49)
b_{MACRO}	-0.15	-6.22**	-2.19	-18.74	5.90	-2.06	0.01	0.02	2.40	-10.27**	-1.78
	(-1.40)	(-1.98)	(-1.32)	(-0.48)	(0.95)	(-0.10)	(0.40)	(0.38)	(0.53)	(-2.28)	(-0.71)
b_{MKT}	2.61*	5.83***	4.91***	1.68	1.49	3.65*	2.17**	2.16	1.23	7.70***	3.61**
	(1.87)	(3.31)	(2.77)	(0.97)	(0.48)	(1.71)	(2.40)	(1.59)	(0.25)	(3.49)	(2.22)
SSQE	0.99	0.49	0.61	1.10	0.78	0.85	1.80	1.10	0.84	0.85	1.95
MAPE	1.56	1.12	1.18	1.69	1.45	1.54	2.05	1.65	1.52	1.53	2.35

Panel D: Risk premia using VW returns on 25 PPE–PROF portfolios

	TFP	IST	RD	CAY	LIQ	UNC	ICS	LEV	CRAT	RS	HYS
b_{BW}	3.91	0.22	1.03	5.51	1.75	2.44*	-2.70	1.36	1.78	1.64	5.72
	(1.20)	(0.19)	(0.86)	(1.63)	(1.04)	(1.90)	(-0.61)	(0.46)	(1.41)	(1.23)	(1.61)
b_{MACRO}	-0.17*	-6.33**	-2.64*	72.79*	10.56**	6.63	0.02	0.06	4.28	-12.05*	2.40
	(-1.90)	(-2.16)	(-1.75)	(1.66)	(2.14)	(0.50)	(0.75)	(1.37)	(1.03)	(-1.85)	(0.84)
b_{MKT}	2.73**	5.39***	4.90***	4.31**	-1.09	3.72***	2.25**	2.09*	-1.40	7.76***	2.08
	(2.19)	(3.14)	(2.91)	(2.47)	(-0.41)	(2.73)	(2.50)	(1.74)	(-0.30)	(2.96)	(1.29)
SSQE	0.96	0.71	0.67	0.96	0.61	1.04	1.20	1.04	1.01	1.05	1.86
MAPE	1.45	1.12	1.14	1.62	1.21	1.48	1.52	1.55	1.43	1.47	2.07

Note: This table presents GMM estimates of the SDF factor loadings and pricing errors from asset pricing models (Equation (4)) in which the SDF is a linear combination of the market factor (MKT), the equity-market sentiment (BW) factor, and an additional macroeconomic shock ($MACRO$). Each column in the table corresponds to a different model (i.e., different choice of $MACRO$) from the following list: (1) TFP: utilization-adjusted total factor productivity shocks [Fernald (2012)], (2) IST: investment-specific technology shocks [Papanikolaou (2011)], which we estimate as the return spread between investment- and consumption-good producing firms, (3) CAY: consumption-wealth ratio [Lettau and Ludvigson (2001)], (4) LIQ: aggregate liquidity [Pastor and Stambaugh (2003)], (5) UNC: macroeconomic uncertainty shocks [Jurado et al. (2015)], (6) ICS: aggregate equity financing shocks [Belo et al. (2019)], (7) LEV: financial intermediary leverage factor [Adrien et al. (2014)], (8) CRAT: financial intermediary capital ratio factor [He et al. (2017)], (9) RS: production network risk factor [Grigoris et al. (2023)], which we estimate as the return spread between firms with high vs low receivables-to-sales ratios, (10) BW: equity market sentiment [Baker and Wurgler (2006)], (11) HYS: credit market sentiment, which we measure using the aggregate share of high-yield new bond issuances as in Greenwood and Hanson (2013). Each panel uses a different set of test assets to estimate each model. We use 25 test assets in each panel, constructed using 5 by 5 bivariate (independent) sorts on profitability and one of AG, INVT, AREC, and PPE respectively. We use NYSE quintile cutoffs to form the test asset portfolios. As measures of fit, we report the sum of squared (pricing) errors (SSQE) implied from each model, as well as the mean absolute pricing errors (MAPE). These measures of fit have been annualized, so they are comparable across models. As a point of reference, we also report results using the CAPM (i.e., no BW and $MACRO$ factors in Equation (4)) in the first column of each panel. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Bolton et al. (2013) where firms must respond to stochastic financing conditions, not just productivity shocks. The main challenge is to understand why, in the context of such models, the performance of the PPE-based factor is inferior to that of the AG, INVT, and AREC-based factors. While we acknowledge the difficulty of ruling out alternatives, below we discuss a few possible explanations for our main findings building on several results from the extant literature.

We believe that, in the context of our study, a key difference between short-term assets (INVT and AREC) and long-term assets (PPE) is their differential value as collateral for debt financing. We hypothesize that a firm's AREC and INVT may provide more information about the firm's ability to access the debt market than its PPE based on the evidence in Berger et al. (1996). The authors use data on the proceeds from discontinued operations for a sample of manufacturing firms from

1984 to 1993 and show that the recovery value for a dollar of fixed assets (PPE) is lower than that of a dollar of accounts receivable (AREC) or inventory (INVT). Campello and Hackbarth (2012) use this idea to construct a firm-level index of asset tangibility as a proxy for the firm's ability to pledge collateral. Based on the evidence in Berger et al. (1996), and consistent with our hypothesis, the collateralizability proxy constructed by Campello and Hackbarth (2012) is more sensitive to changes in AREC and INVT than to changes in PPE.

Ai et al. (2020) argue that asset collateralizability should command a negative premium and they show empirical evidence consistent with this idea. They point out that many macroeconomic models featuring financing frictions predict that financial constraints are more binding in recessions and therefore can worsen economic downturns. Through their ability to relax financial constraints, collateralizable assets should provide a hedge against the risk of becoming financially constrained in recessions. Hence, firms with more collateralizable assets should be less exposed to aggregate financing shocks. If, consistent with Berger et al. (1996) and Campello and Hackbarth (2012), AREC and INVT provide a better proxy than PPE for the firms' collateralizable capital, then the results in Ai et al. (2020) could explain why we find a stronger link between financing shocks and AREC and INVT. In the Ai et al. (2020) framework, the AREC and INVT (and, by extension AG) factors would simply be better proxies for the collateralizability premium.

Nevertheless, since the Ai et al. (2020) study does not model the role of *equity* financing costs in particular, it can not explicitly account for the central role the equity-market sentiment factor plays in our main findings. We believe that the economic mechanism proposed in Belo et al. (2019) may close that gap. The authors suggest (and find evidence consistent with) the idea that high-investment firms should have a lower sensitivity to aggregate equity financing costs because they are less collateral constrained than low-investment firms. This means they should be better able to substitute equity for debt financing when faced with increases in the costs of equity financing. Hence, firms with more collateralizable assets should be less exposed to aggregate equity financing shocks.

While Belo et al. (2019) use investments in long-term assets (CAPX) in their study, we argue that their mechanism should apply to all the other collateralizable assets of the firm. Furthermore, since, based on Berger et al. (1996), INVT and AREC are more collateralizable than PPE, sorting on INVT, and AREC (and, by extension, AG) could simply provide more accurate sorts on the extent to which firms are collateral constrained. Put differently, the inferior performance of the PPE-based factor may be due to its larger measurement error as a proxy for firms' ability to substitute equity for debt.

We explore this channel in Table 8 where we report average debt and equity issuance levels for firms in the top and bottom quintiles of AG (Panel A), INVT (Panel B), AREC (Panel C), and PPE growth (Panel D).[22] Following the methodology in Belo et al. (2019), we control for the effect of business cycle shocks on issuance activity by orthogonalizing each quintile-level time-series of average issuance on the annual growth in real GDP.[23] We then report averages for these orthogonalized series, calculated separately for periods with high versus low sentiment shocks. Periods with high (low) sentiment shocks are the years falling in the top (bottom) decile with respect to the BW factor employed in our GMM tests (averaged out over the year). All numbers reported are in percentage points.

[22] Equity issuance is calculated as the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTK). Debt issuance is calculated as the change in total long-term debt outstanding (DLTT) plus the change in long-term debt due within one year (DLC). Both issuance variables are scaled by lagged total assets and are winsorized at the 1st and 99th percentiles.

[23] Specifically, each orthogonalized series is obtained by taking the intercept plus the residual from a regression of the non orthogonalized average-issuance series on real GDP growth.

Table 8
Average Issuance Conditioning on Equity-Market Sentiment.

Panel A: Average issuance by AG quintile				
	Equity issuance		Debt issuance	
	AG(Q1)	AG(Q5)	AG(Q1)	AG(Q5)
High sentiment periods (BW)	6.71	8.09	-0.03	5.01
Low sentiment periods (BW)	4.24	4.03	-0.01	5.81
High - Low	-2.48	-4.05	0.02	0.80
Percent change	-36.88	-50.12	76.06	15.86
Panel B: Average issuance by INVT quintile				
	Equity issuance		Debt issuance	
	INVT(Q1)	INVT(Q5)	INVT(Q1)	INVT(Q5)
High sentiment periods (BW)	3.49	5.85	0.50	3.26
Low sentiment periods (BW)	2.22	3.28	0.61	4.30
High - Low	-1.27	-2.57	0.11	1.05
Percent change	-36.33	-43.89	22.54	32.17
Panel C: Average issuance by AREC quintile				
	Equity issuance		Debt issuance	
	AREC(Q1)	AREC(Q5)	AREC(Q1)	AREC(Q5)
High sentiment periods (BW)	4.78	5.87	0.80	3.15
Low sentiment periods (BW)	2.82	3.07	0.72	4.44
High - Low	-1.96	-2.80	-0.08	1.29
Percent change	-41.01	-47.67	-10.06	41.03
Panel D: Average issuance by PPE quintile				
	Equity issuance		Debt issuance	
	PPE(Q1)	PPE(Q5)	PPE(Q1)	PPE(Q5)
High sentiment periods (BW)	6.04	6.25	0.19	5.57
Low sentiment periods (BW)	3.44	3.70	-0.10	5.91
High - Low	-2.60	-2.55	-0.28	0.33
Percent change	-43.00	-40.83	-151.00	6.00

Note: This table presents average debt and equity issuance for the top and bottom quintiles of asset growth (Panel A), inventory growth (Panel B) accounts receivable growth (Panel C) and PPE growth (Panel D). To obtain these averages, we first calculate cross-sectional averages of debt and equity issuance at the quintile-year level. We then orthogonalize each resulting time-series of averages by regressing them on a constant and GDP growth and taking the intercept plus the residual from these regressions. The table reports the means of these orthogonalized series during periods with low equity market sentiment and high equity market sentiment. Periods with low (high) sentiment are the years in our sample which fall in the bottom (top) decile with respect to the Baker and Wurgler (2006) factor described in Section 4. Equity issuance is calculated as the purchase of common and preferred stock (SSTK) minus the sale of common and preferred stock (PRSTK). Debt issuance is calculated as the change in total long-term debt outstanding (DLTT) plus the change in long-term debt due with one year (DLC). Both issuance variables are scaled by lagged total assets. The sample period is from 1972 to 2018. All numbers reported are in percentage points.

Across all panels, the results in Table 8 are consistent with the debt-substitution channel in Belo et al. (2019). Namely, when faced with higher equity financing costs (low sentiment), firms in both quintiles (Q1 and Q5) issue less equity, but only firms in the top quintile (Q5) are able to substitute that with higher debt issuance. The debt issuance of firms in the bottom quintile (Q1) remains virtually unchanged, and very close to zero.

Importantly for our study, this substitutability seems to be stronger when we use AG, INVT, and AREC sorts (panels A, B, and C) than when we use PPE sorts (bottom panel). This result seems to be driven mainly by the behavior of firms in Q5 (second and fourth column). Specifically, during low sentiment periods, firms in AG(Q5), INVT(Q5) and AREC(Q5) seem to reduce equity issuance relatively more than firms in PPE(Q5) (50%, 43%, and 47% respectively for AG, INVT, and AREC, versus 40% for PPE) and they seem to increase debt issuance by relatively more (15%, 32%, and 41% respectively for AG, INVT, and AREC, versus only 6% for PPE). This is consistent with our hypothesis that AG, INVT, and AREC may simply be better proxies than PPE for the extent

Table 9
Using Sharpe Ratio Tests to Compare HXZ and FF5F to Traditional Factor Models Conditioning on DOX.

Panel A1: Comparing HXZ-like models when DOX is above median						
Baseline model	Statistic	CAPM	FF3F	C4F	HXZ	FF5F
HXZ(AG)	$\Delta(maxSR^2)$	-0.125***	-0.103**	-0.091***		-0.003
	p-value	(0.008)	(0.012)	(0.010)		(0.939)
Panel A2: Comparing HXZ-like models when DOX is below median						
Baseline model	Statistic	CAPM	FF3F	C4F	HXZ	FF5F
HXZ(AG)	$\Delta(maxSR^2)$	-0.162***	-0.110*	-0.013		-0.067
	p-value	(0.005)	(0.064)	(0.823)		(0.198)
Panel B1: Comparing FF5F-like models when DOX is above median						
Baseline model	Statistic	CAPM	FF3F	C4F	HXZ	FF5F
FF5F(AG)	$\Delta(maxSR^2)$	-0.122***	-0.101**	-0.088**	0.003	
	p-value	(0.007)	(0.016)	(0.030)	(0.939)	
Panel B2: Comparing FF5F-like models when DOX is below median						
Baseline model	Statistic	CAPM	FF3F	C4F	HXZ	FF5F
FF5F(AG)	$\Delta(maxSR^2)$	-0.095**	-0.043	0.053	0.067	
	p-value	(0.026)	(0.196)	(0.342)	(0.198)	

Note: In this table we use maximum Sharpe ratio tests as in Barillas et al. (2020) to compare the performance of the HXZ and FF5F models with that of traditional factor models. Specifically, the models we use in these tests are the CAPM, the Fama and French (1993) three factor model (FF3F), the Carhart (1997) four factor model (C4F), the Hou et al. (2015) four factor model (HXZ), and the Fama and French (2015) five factor model (FF5F). In each panel, we report the difference in squared maximum Sharpe ratios between the model specified in the column header and the model specified in the row header. These Sharpe ratios are calculated in periods with above-median DOX (i.e., high overextrapolation) in panels A1 and B1, and in periods with below-median DOX (i.e., low overextrapolation) in panels A2 and B2. Panels A1 and A2 construct factors as in HXZ and panels B1 and B2 construct factors as in FF5F. p-values are reported in parentheses and are calculated as in Barillas et al. (2020).

to which firms can substitute equity for debt when facing increases in equity financing costs.

It is important to acknowledge that this debt-equity substitution channel operates independently of the macroeconomic forces that may be causing changes in equity financing costs. As pointed out in Belo et al. (2019), this includes forces like time-varying information asymmetry, agency frictions, liquidity, and risk aversion, but they may also include mispricing shocks caused by various investor behavioral biases. Our final set of tests explores this idea by using the aggregate "degree of overextrapolation" (DOX) metric of Cassella and Gulen (2018) and investigating if the performance of the AG-based factor models differs based on the degree of overextrapolation in the economy.[24]

In Table 9, we test if the superior performance of HXZ and FF5F over the traditional models (CAPM, FF3F, and C4F) varies depending on whether we are in a high or low overextrapolation period (i.e., above or below-median DOX level). We use model comparison tests based on the maximum squared Sharpe ratio analogous to the ones in Table 1, the only difference being that in Table 9, the Sharpe ratios are calculated separately during high DOX times (Panels A1 and B1) and during low DOX times (Panel A2 and B2). Panels A1 and A2 use HXZ as the baseline model and Panels B1 and B2 use FF5F as the baseline model. Panel A1 shows that, when DOX is high, the HXZ model performs significantly better than the CAPM, FF3F, and C4F (FF5F performs about the same as HXZ). However, Panel A2 shows that, when DOX is low, HXZ performs no better than the C4F model and is only marginally better than the FF3F model (the difference is significant only at the 10% level). Similarly, in Panel B1, when DOX is high, we see that the FF5F model performs significantly better than the CAPM, FF3F, and C4F models. However, Panel B2 shows that, when DOX is low, the FF5F model performs no better than the FF3F model or the C4F model. Overall, the results in Table 9 suggest that including an AG factor in our models only provides improvements in pricing when the economy is in an overextrapolative state.[25]

[24] Specifically, DOX measures the relative weight investors place on recent versus distant past returns when forming expectations about future stock market returns. It is estimated recursively from surveys of expectations of stock market returns in the U.S. modeled as $Exp_t = a + b\sum_{i=0}^{L} w_i R_{t-(i+1)\Delta t, t-i\Delta t}$ where $w_i = \frac{\lambda^i}{\sum_{k=0}^{L}\lambda^k}$ and $0 \le \lambda < 1$. Exp_t refers to investors' survey expectations at time t (taken from the survey of retail investors from the American Association of Individual Investors and the Investor Intelligence Survey). $R_{i,j}$ is the realized return on the S&P 500 index between time i and time j. Δt is the frequency of return observations, and it is set to $1/4$ (i.e., quarterly returns). The model is estimated using nonlinear least squares to obtain λ, the (geometric) decay parameter measuring relative weight investors place on recent versus distant past returns. DOX is measured as $1-\lambda$, a higher value of which implies that investors place too much weight on recent past and hence high degree of overextrapolation. The estimation is done recursively (every month) over three different estimation windows L, and the estimates are combined using the methodology in Pesaran and Timmermann (2007) and Capistran and Timmermann (2009). See Cassella and Gulen (2018) and Greenwood and Shleifer (2015) for more details on the estimation method.

[25] In Table E13 in the Appendix, we repeat the test-asset pricing analysis in Table E1, this time calculating each test statistic separately during periods of high and low DOX. The results show similar conclusions to Table 9: the HXZ and FF5F models provide a superior performance to the traditional models only during times over high overextrapolation. For example, when DOX is high, using HXZ (FF5F) we can explain all but one (four) out of our 35 anomalies, whereas the best we can do using the traditional models is with the Carhart (1997) model (C4F), which explains all but 12 anomalies. However, when DOX is low, the HXZ (FF5F) model explains all but 10 (22) anomalies, while the C4F model explains all but 14 anomalies.

Table 10
Using Sharpe Ratio Tests to Compare HXZ and FF5F to Models Using Alternative Investment Factors Conditioning on DOX.

Panel A1: Comparing HXZ-like models when DOX is above median							
Baseline model	Statistic	None	CAPX	PPE	TOTK	PHK	INTK
HXZ(AG)	$\Delta(maxSR^2)$	-0.067*	-0.045*	-0.060**	-0.058**	-0.065**	-0.062*
	p-value	(0.051)	(0.092)	(0.029)	(0.024)	(0.024)	(0.063)
Panel A2: Comparing HXZ-like models when DOX is below median							
Baseline model	Statistic	None	CAPX	PPE	TOTK	PHK	INTK
HXZ(AG)	$\Delta(maxSR^2)$	-0.094**	-0.024	-0.008	0.000	-0.040	-0.028
	p-value	(0.025)	(0.445)	(0.778)	(0.993)	(0.200)	(0.449)
Panel B1: Comparing FF5F-like models when DOX is above median							
Baseline model	Statistic	None	CAPX	PPE	TOTK	PHK	INTK
FF5F(AG)	$\Delta(maxSR^2)$	-0.074**	-0.067**	-0.077**	-0.076**	-0.074**	-0.078**
	p-value	(0.041)	(0.043)	(0.030)	(0.026)	(0.027)	(0.034)
Panel B2: Comparing FF5F-like models when DOX is below median							
Baseline model	Statistic	None	CAPX	PPE	TOTK	PHK	INTK
FF5F(AG)	$\Delta(maxSR^2)$	0.001	0.004	0.002	0.002	0.009	-0.003
	p-value	(0.928)	(0.693)	(0.830)	(0.803)	(0.434)	(0.728)

Note: In this table we use maximum Sharpe ratio tests as in Barillas et al. (2020) to compare the performance of the HXZ and FF5F models with that of models based on alternative investment measures. In each panel, we report the difference in squared maximum Sharpe ratios between the model specified in the column header and the model specified in the row header. These Sharpe ratios are calculated in periods with above-median DOX (i.e., high overextrapolation) in panels A1 and B1, and in periods with below-median DOX (i.e., low overextrapolation) in panels A2 and B2. Panels A1 and A2 construct factors as in HXZ and panels B1 and B2 construct factors as in FF5F. The alternative measures of investment we use are: capital expenditures divided by lagged PPE ("CAPX" column), the percentage growth in PPE ("PPE" column), the percentage growth in total capital ("TOTK" column), the change in total physical capital divided by lagged total capital ("PHK" column), and the change in total intangible capital divided by lagged total capital ("INTK" column). For the last three measures, total capital, total physical capital, and total intangible capital are measured as in Peters and Taylor (2017). p-values are reported in parentheses and are calculated as in Barillas et al. (2020).

In Table 10, we look at versions of HXZ and FF5F built using alternative measures of investment, and we compare their performance with the original models in times of high and low overextrapolation. The fact that all the estimates in the first row of Panel A1 are significantly negative shows that, during high DOX times, the HXZ model constructed using any of the alternative investment measures performs significantly worse than the original, AG-based HXZ model. Panel A2 shows that this is not the case during low DOX periods: the HXZ model performs no better whether we use AG to create the investment factor or any of the alternative measures of investment. Panels B1 and B2 find the same pattern when we compare FF5F-style models: the AG-based model (FF5F) performs significantly better than all the alternatives (Panel B1) in high DOX times, but not during low DOX times (Panel B2). These results help support the prior finding that the superior performance of the AG-based models is confined to the half of our sample when the degree of overextrapolation is high.[26]

To alleviate the concern that these results are confined to the five specific measures of investment used in Table 10, in Fig. 2 we use all the 144 alternative measures of investment described in Section 2.2. Specifically, the figure shows histograms of the maximum squared Sharpe ratios that can be obtained with the factors in each of the 144 models, both during high-DOX times (leftmost panels) and during low-DOX times (rightmost panels). The top two panels use HXZ-style models and the bottom two panels use FF5F-style models. The top-left panel in Fig. 2 shows that, during high DOX periods, the HXZ model (marked with the vertical "AG" line) is an extreme outlier when compared to the other 143 models providing a significantly higher maximum squared Sharpe ratio. The top-right panel shows that this is not the case during low-DOX periods, with the HXZ model performing similarly to the alternative investment models. The bottom panels in the figure show that the same finding holds when we compare FF5F-style models. The FF5F model is by far the best model when DOX is high (bottom-left panel) but about in the middle of the distribution when DOX is low (bottom-right panel).

6. Conclusion

Uncovering firm characteristics that predict future stock returns has a long tradition in the asset pricing literature. Using these characteristics to construct new factor models usually leads to an improved ability to describe the cross-section of average returns, at least in-sample, and for a particular subset of test assets. However, without understanding the structural mechanisms through which this improved pricing ability comes about, it is difficult to make prescriptions as to how the new models should be used, or to claim that they lend new insights into how assets are priced. This motivates us to investigate what may be driving the explanatory power of the HXZ and FF5F models, as they are quickly becoming the new benchmark factor pricing models.

We focus on the investment factor, which is constructed using growth in total assets in the original HXZ and FF5F papers. We start by documenting that the performance of this asset growth factor declines significantly if it was constructed using virtually any other previously proposed measure of investment. Furthermore, breaking the AG measure down into its main subcomponents and constructing factors using those subcomponents reveals a surprising fact: the performance of the HXZ and FF5F models deteriorates significantly when the investment

[26] In Table E14 in the Appendix, we test model performance conditional on overextrapolation using anomaly portfolios and bivariate sorts as test assets. The results are consistent with the findings in Table 10. The original AG-based models perform significantly better during high-DOX periods but not during low-DOX periods.

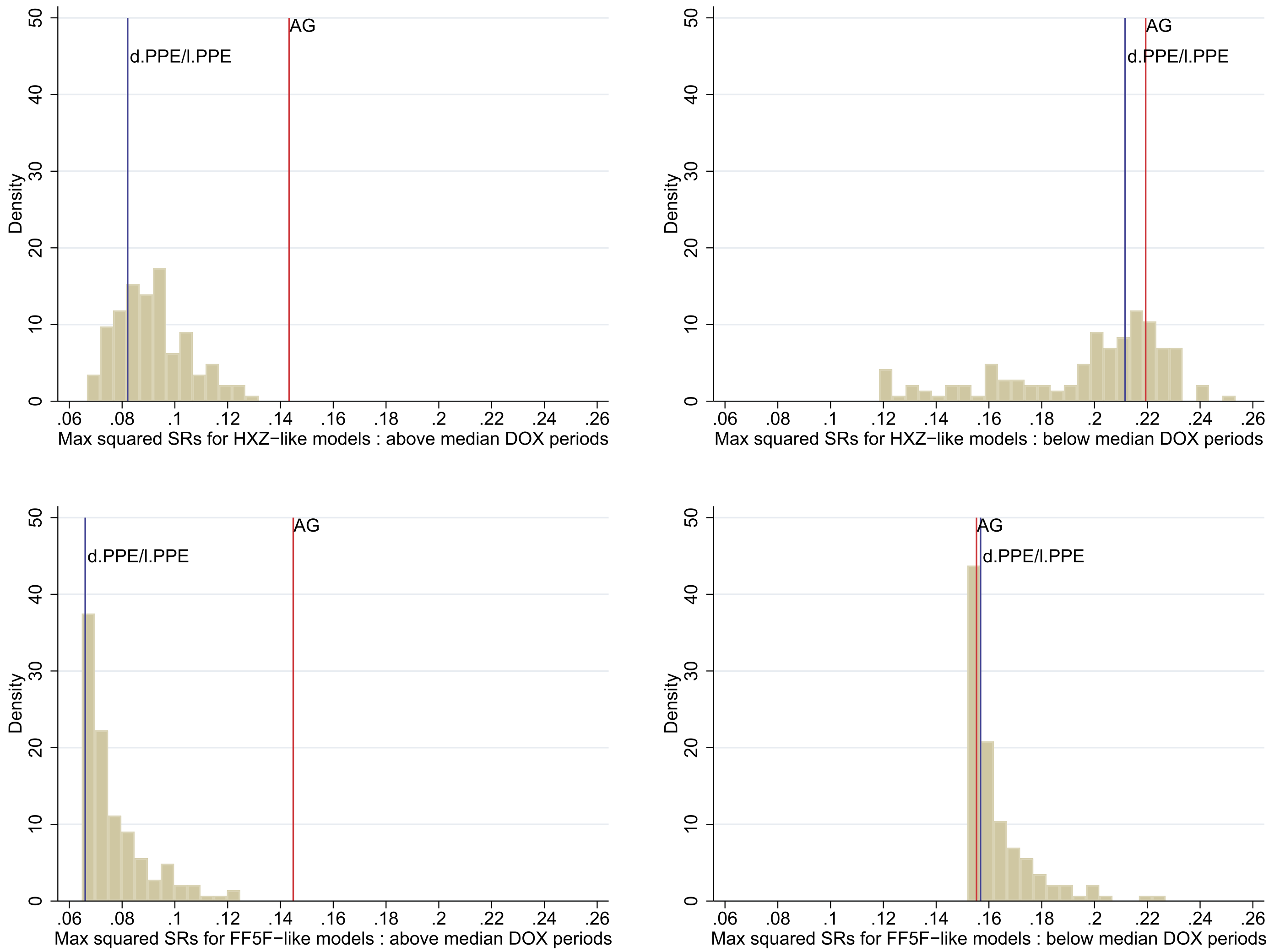

Fig. 2. Performance of alternative HXZ- and FF5F-Style Models Conditioning on DOX. *Note*: This figure plots the performance of HXZ-style models (top panels) and FF5F-style models (bottom panels) obtained by replacing the asset-growth-based investment factor in HXZ and FF5F, with a factor based on one of 144 alternative measures of investment. The figures report histograms of maximum squared Sharpe ratios ("SRs") that can be obtained with the factors in each alternative model. In the panels on the left, these Sharpe ratios are calculated using time periods when DOX is above its sample median (i.e., high overextrapolation) and in the panels on the right, they are calculated using time periods when DOX is below its sample median (i.e., low overextrapolation). As reference points, the red vertical lines show the performance of the original, asset-growth-based HXZ and FF5F models and the blue lines show the performance of the models obtained using the percentage change in PPE to construct the investment factor.

factor is constructed using growth in PPE but not when using growth in inventory (INVT) and accounts receivable (AREC). The finding that the performance of the AG factor does not decline when we completely ignore information about investment in long-term assets calls into question the idea that its explanatory power is primarily attributable to a structural link between expected returns and investment activity.

These findings motivate us to investigate a different structural link between asset growth and expected returns. We use a broad set of macroeconomic factors to price portfolios sorted on AG, INVT, AREC, and PPE growth and find that financing shocks help price AG, INVT, and AREC portfolios but not PPE portfolios. In particular, the equity-market sentiment factor seems to drive out the pricing power of almost all other factors when pricing AG, INVT, and AREC portfolios, but not PPE portfolios. We argue that this finding is consistent with the economic mechanism in Belo et al. (2019), who propose that high-investment firms are less exposed to equity financing costs because they are less collateral constrained than low-investment firms, and hence can better substitute equity for debt financing when equity financing becomes more costly. Since INVT and AREC are more collateralizable than PPE, they (and by extension AG) may provide better proxies than PPE for the firm's sensitivity to equity financing costs. Supporting this hypothesis, we find that, compared to PPE sorts, sorting on AG, INVT, and AREC provides larger spreads in the extent to which firms substitute equity for debt financing when facing low equity market sentiment.

This debt-equity substitution channel linking AG, INVT, and AREC to equity financing costs is agnostic to the underlying causes that may be driving these financing costs. It is important to acknowledge that these underlying causes may very well include systematic behavioral biases. We present some suggestive (though by no means causal) evidence to this effect by using an aggregate measure of overextrapolation and showing that the superior performance of the asset growth factor is confined to the half of our sample with above-median levels of overextrapolation. In fact, in the sample with below-median overextrapolation, HXZ does not perform significantly better than the Carhart (1997) model and FF5F does not perform significantly better than the Fama and French (1993) model.

Nevertheless, we acknowledge that, in the absence of a structural model, it is very difficult to conclude whether a factor model is driven by risk or mispricing, and our results suggest that further investigation is warranted along these lines with respect to the HXZ and FF5F models.

More generally, our findings indicate that caution should be exercised when using reduced-form models to interpret the economic forces captured by asset pricing factors. Though the present value and q models used in HXZ and FF5F are certainly intuitive, our study shows that the investment factor they propose may, in fact, be capturing forces that are outside their scope.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The codes and data of the article can be found at https://doi.org/10.17632/tzxtm6ys99.1.

Appendix. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2023.103746.

References

Adrien, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. J. Finance 69, 2557–2596.
Ai, H., Li, J.E., Li, K., Schlag, C., 2020. The collateralizability premium. Rev. Financ. Stud. 33, 5821–5855.
Alti, A., Tetlock, P., 2014. Biased beliefs, asset prices, and investment: a structural approach. J. Finance 69, 325–361.
Asker, J., Farre-Mensa, J., Ljungqvist, A., 2015. Corporate investment and stock market listing: a puzzle? Rev. Financ. Stud. 28, 342–390.
Baker, M., Stein, J., Wurgler, J., 2003. When does the market matter? Stock prices and the investment of equity-dependent firms. Q. J. Econ. 118, 969–1005.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680.
Barillas, F., Kan, R., Robotti, C., Shanken, J., 2020. Model comparison with Sharpe ratios. J. Financ. Quant. Anal. 55, 1840–1874.
Barillas, F., Shanken, J., 2017. Which alpha? Rev. Financ. Stud. 30, 1316–1338.
Belo, F., Lin, X., Yang, F., 2019. External equity financing shocks, financial flows, and asset prices. Rev. Financ. Stud. 32, 3500–3543.
Berger, P., Ofek, E., Swary, I., 1996. Investor valuation and abandonment option. J. Financ. Econ. 42, 257–287.
Bolton, P., Chen, H., Wang, N., 2013. Market timing, investment, and risk management. J. Financ. Econ. 109, 40–62.
Campello, M., Hackbarth, D., 2012. The firm-level credit multiplier. J. Financ. Intermed. 21, 446–472.
Capistran, C., Timmermann, A., 2009. Disagreement and biases in inflation expectations. J. Money Credit Bank. 41, 365–396.
Carhart, M., 1997. On persistence in mutual fund performance. J. Finance 52, 57–82.
Cassella, S., Gulen, H., 2018. Extrapolation bias and the predictability of stock returns by price-scaled variables. Rev. Financ. Stud. 31, 4345–4397.
Cochrane, J., 1991. Production-based asset pricing and the link between stock returns and economic fluctuations. J. Finance 46, 209–237.
Cochrane, J., 2005. Asset Pricing, revised edition. Princeton University Press, Princeton, NJ.
Cooper, M., Gulen, H., Schill, M., 2008. Asset growth and the cross-section of stock returns. J. Finance 63, 1609–1652.
Denis, D., Sibilkov, V., 2010. Financial constraints, investment, and the value of cash holdings. Rev. Financ. Stud. 23, 248–269.
Eisfeldt, A., Papanikolaou, D., 2014. The value and ownership of intangible capital. Am. Econ. Rev. 104, 189–194.
Elsaify, A., 2017. The Innovation Premium. Unpublished working paper. University of Pennsylvania.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.
Fazzari, S., Hubbard, G., Petersen, B., 1988. Financing constraints and corporate investment. Brookings Pap. Econ. Act. 19, 141–195.
Fernald, J., 2012. A quarterly, utilization-adjusted series on total factor productivity. Federal Reserve Bank of San Francisco Working Paper 2012-19.
Greenwood, R., Hanson, S., 2013. Issuer quality and corporate bond returns. Rev. Financ. Stud. 26, 1483–1525.
Greenwood, R., Shleifer, A., 2015. Expectations of returns and expected returns. Rev. Financ. Stud. 27, 1714–1746.
Grigoris, F., Hu, Y., Segal, G., 2023. Counterparty risk: implications for network linkages and asset prices. Rev. Financ. Stud. 36, 814–858.
He, Z., Kelly, B., Manela, A., 2017. Intermediary asset pricing: new evidence from many asset classes. J. Financ. Econ. 126, 1–35.
Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: an investment approach. Rev. Financ. Stud. 28, 650–705.
Hulten, C., Hao, X., 2008. What is a company really worth? Intangible capital and the “market to book value” puzzle. National Bureau of Economics Research Working Paper 14548.
Jurado, K., Ludvigson, S., Ng, S., 2015. Measuring uncertainty. Am. Econ. Rev. 105, 1177–1216.
Kelly, B., Pruitt, S., Su, Y., 2019. Characteristics are covariances: a unified model of risk and return. J. Financ. Econ. 134, 501–524.
Kogan, L., Papanikolaou, D., 2012. Economic activity of firms and asset prices. Annu. Rev. Financ. Econ. 4, 361–384.
Kozak, S., Nagel, S., Santosh, S., 2019. Shrinking the cross-section. J. Financ. Econ. 135, 271–292.
Lettau, M., Ludvigson, S., 2001. Consumption, aggregate wealth, and expected stock returns. J. Finance 56, 815–849.
Li, D., Zhang, L., 2010. Does q-theory with investment frictions explain anomalies in the cross section of returns? J. Financ. Econ. 98, 297–314.
Liu, L.X., Whited, T.M., Zhang, L., 2009. Investment-based expected stock returns. J. Polit. Econ. 117, 1105–1139.
Lyandres, E., Sun, L., Zhang, L., 2008. The new issues puzzle: testing the investment-based explanation. Rev. Financ. Stud. 21, 2825–2855.
Newey, W.K., West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. Int. Econ. Rev. 28, 777–787.
Papanikolaou, D., 2011. Investment shocks and asset prices. J. Polit. Econ. 119, 639–685.
Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 111, 642–685.
Pesaran, M.H., Timmermann, A., 2007. Selection of estimation window in the presence of breaks. J. Econom. 137, 134–161.
Peters, R.H., Taylor, L.A., 2017. Intangible capital and the investment-q relation. J. Financ. Econ. 116, 1–22.
Warusawitharana, M., Whited, T.M., 2016. Equity market misvaluation, financing, and investment. Rev. Financ. Stud. 29, 603–654.
Zhang, M.X., 2014. Who bears firm-level risk? Implications for cash flow volatility. Unpublished working paper. University of Texas, Austin.