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Moving beyond a narrow definition of value investing

Master Thesis

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Abstract

This study shows that the information content of valuation ratios can be highly dissimilar. It presents a value measure that outperforms book-to-market not only in terms of the abnormal returns a zero-cost portfolio formed on this sorting variable generates relative to factor models, but also in terms of its ability to capture firms with a high level of profitability and a strong profitability persistence. In addition, portfolios double sorted on profitability and value are used to move beyond the traditional definition of value investing. Long-only portfolios formed on profitability and book-to-market, however, do not help in separating winners from losers among value stocks. Instead, they rather predispose investors to firms with temporarily inflated accounting numbers. The abnormal returns that zero-cost portfolios double sorted on profitability and book-to-market generate relative to a Fama and French (2015) five-factor model are overwhelmingly due to the model's failure to price the lowest quintile portfolios. On the other hand, factor models face similar problems in pricing long-only portfolios formed on the basis of profitability and enterprise-value-deflated cash-based operating profitability. These portfolios consistently generate positive abnormal returns relative to the considered factor models. The results are difficult to reconcile with explanations based on the value premium as the corresponding portfolio firms resemble growth stocks in terms of both characteristics and covariances. These firms exhibit a high level of profitability and a strong profitability persistence after portfolio formation.

Keywords: Value investing, asset pricing, fundamental analysis, profitability persistence

JEL Classifications: G11, G12, and M41

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1 Introduction

Following the findings of Basu (1977), Rosenberg et al. (1985), and Fama and French (1992), amongst others, research in finance has been primarily concerned with the value premium and its implications on market efficiency. For instance, Fama and French (1993) show that the abnormal returns of low P/E, low P/C, and low sales growth stocks are well captured by size and book-to-market, and that these anomalies largely disappear in a Fama and French (1993) three-factor model. Ever since, literature refers to the value premium as the difference in returns of high-minus-low book-to-market stocks and value continues to be used as a risk-factor in asset pricing models. For instance, consistent with a risk-based interpretation, Fama and French (1992) and Penman (1996) observe an inverse relation between B/M portfolios, future earnings, and future growth rates. Their conclusive studies are complemented by a vast amount of evidence on differential sensitivities of growth and value stocks to time-varying macro-economic risks. Collectively, they suggest that the outperformance of B/M stocks might merely be an artefact of risk factor exposures. (e.g., Campbell et al. 2010, Cohen et al. 2009, Petkova and Zhang 2005, Zhang 2005)

While these risk-based explanations of the traditional value premium are comprehensive and sound, this stream of literature does not account for a broader definition of value and rather considers different price ratios as just different ways to scale a stock's price with a fundamental. Graham and Dodd (1934), however, argue that: "An investment operation is one which, upon thorough analysis, promises safety of principal and a satisfactory return." Firms with high book-to-market, on the other hand, tend to be persistently distressed (e.g., Fama and French 1998) and without any further fundamental investment restrictions in place, an investment therein might not promise safety of principal. If anything, according to the findings of Kok et al. (2017), high B/M ratios systematically identify securities with overstated book value that is subsequently written down.

Hence, the aim of this thesis is to highlight that the information content of various valuation measures can be highly dissimilar. Correspondingly, this study will provide evidence on noticeable differences among value portfolios when it comes to their respective firm characteristics, average monthly excess returns, risk factor exposures, and persistence in profitability among portfolio firms. This thesis will present with enterprise-value-deflated cash-based operating profitability a value measure that outperforms book-to-market in terms of the abnormal returns a zero-cost portfolio formed on this sorting variable generates relative to factor models, and in terms of its ability to capture firms with a high level of profitability and a strong profitability persistence. In addition, this valuation ratio not only subsumes other value measures in predicting the cross-section of average returns, but similar to lagged-assets-deflated cash-based operating profitability, also subsumes the power of accruals in predicting returns. The latter observation is inconsistent with the hypothesis of Sloan (1996) that investors fail to distinguish the accrual from a more persistent cash flow component. Instead, in line with the conclusion of Ball et al. (2016), this evidence is collectively indicating that accruals allow the regression to extract the cash-based component from the accruals-based profitability variable. Hence, this study is challenging prior research which considers the accruals anomaly to be distinct and incremental to other anomalies. (e.g., Richardson et al. 2010)

Still, as the firms included in a zero-cost portfolio sorted on enterprise-value-deflated cash-based operating profitability resemble high book-to-market firms in terms of both characteristics and covariances, part of its strong return performance remains subject to the risk-based explanations of the value premium. Hence, by considering the profitability and value dimension jointly, this study moves beyond traditional value investing and proposes two-dimensional investment strategies whose portfolio firms resemble low book-to-market firms in terms of both characteristics and covariances. Thus, it is even more difficult to reconcile their strong return performance with the mentioned risk-based explanations of the value premium. Thereby, this thesis aims to capture the effective value investing strategies of contemporary value investors such as Warren Buffett who adjust a traditional value strategy for other quality criteria. The term “contemporary value investors” was coined by Greenwald et al. (2004) and is used in this study to refer to investors who consider value investing as purchasing highly profitable firms at low valuation ratios.

This joint consideration of the profitability and value dimension is in line rather than in conflict with the original conception of value investing according to Graham and Dodd (1934), which has never been grounded on a mechanical low multiple investment approach exclusively. Instead, according to their investment philosophy, statistical measures that indicate cheapness render themselves necessary but insufficient to constitute a successful investment operation. In line with this reasoning, Kok et al. (2017) argue that by the 1990’s the term value investing started to be used misleadingly to describe simple mechanical investment strategies, rather than to refer to an investment operation that is concerned with identifying discrepancies between a stock’s price and its intrinsic value. Hence, instead of being overly dependent on one specific definition of value investing, this study empirically investigates whether the various formulaic investment strategies that proclaim to align the investment principles of contemporary investors, such as the Magic Formula proposed by Greenblatt (2010) based on an earnings yield and return on capital employed, live up to their proposition. Not the least because the computation of intrinsic value requires detailed knowledge of company and industry economics does scepticism about formulaic investment strategies among contemporary value investors prevail. For instance, Graham and Dodd (1934) repeatedly emphasise the importance of determining the future earning power of a company, a phrase which imposes to their connotation a fairly confident expectation of future results, for which it is insufficient to know what the past earnings have averaged. (Graham and Dodd 1934)

However, the logical and dependable standards that are necessary for an investment strategy to align with the investment principles of contemporary value investors might be very well captured by a combination of persistent fundamental strength and contrarian investing as inter alia documented by Lakonishok et al. (1994). In fact, this thesis will present long-only portfolios double sorted on profitability and enterprise-value-deflated cash-based operating profitability which consistently generate positive abnormal returns relative to the considered factor models. Instead of revealing temporarily inflated accounting numbers among portfolio firms, the evidence points to a failure of asset pricing models to price these trading strategies. The firms included in the long-only portfolios have a high level of profitability across all considered profitability dimensions and show a strong profitability persistence after portfolio formation. If anything, these firms not only resemble growth stocks in terms of both characteristics and covariances, but also in terms of the strong positive profitability growth they exhibit subsequent to portfolio formation.

On the other hand, long-only portfolios formed on the basis of profitability and book-to-market do not help in separating winners from losers among value stocks, as they rather predispose investors to firms with temporarily inflated accounting numbers. This study therefore complements and extends the findings of Novy-Marx (2014) by considering the profitability and value dimension jointly. Moreover, it incrementally adds to the evidence of Ball et al. (2016) by showing that the desirable properties of cash-based operating profitability persist when using a conceptually and fundamentally different deflator, or enterprise value instead of book value of assets, more specifically.

While both the accounting and finance literature have been focused on errors-in-expectations of investors, such as an underreaction to the strength in fundamentals or the extrapolation of past growth into the future, synergies among these findings have remained rather marginal. The following literature review will first shed light on the findings of accounting research concerning fundamental signals that predict future profitability and stock returns, before combined evidence of accounting and finance will be considered.

2 Literature review

2.1 Financial statement analysis and the prediction of stock returns

So far, this thesis has already extensively accentuated the investment philosophy of Graham and Dodd (1934), yet it did not underscore their contribution to research in the area of financial statement analysis. Sloan (1996), amongst others, cites in his paper the advocated implicit distinction between the accrual and cash flow component of earnings which was first made by Graham and Dodd (1962) as the basis of a sound investment operation. Based upon this idea of distinguishing an accrual and a cash flow component of earnings, Sloan (1996) shows that the accrual component is less persistent than the cash flow component and that stock prices fail to fully reflect information contained in the two constituents until subsequent earnings releases. The abnormal returns generated by the accrual strategy are correspondingly clustered around future earnings announcement dates. (Sloan 1996)

Richardson et al. (2005) extend the findings of Sloan (1996) by categorizing accruals according to their reliability. Consistent with their hypothesis, less reliable accruals lead to lower earnings persistence and investors fail to anticipate the lower persistence, ultimately leading to significant mispricing. (Richardson et al. 2005) Similarly, Hirshleifer et al. (2004) emphasize that net operating assets are equal to the sum of cumulative operating accruals and investment, and document weak earnings growth after cumulative net operating income outstrips cumulative free cash flow. Still, stock prices fail to fully reflect the information contained by total-assets-deflated net operating assets. Hence, their evidence complements the findings of Sloan (1996) concerning the accruals anomaly as this measure is a similar strong negative predictor of stock returns. (Hirshleifer et al. 2004) So far, the accruals anomaly returns still cannot be explained by factor models such as the five-factor model of Fama and French (2016). While evidence is not conclusive yet, current literature considers the accruals anomaly to be distinct and incremental to other anomalies. (e.g., Richardson et al. 2010, Fama and French 2016)

Similarly, following the evidence of Ou and Penman (1989) concerning the ability of financial statement summary measures to indicate one-year-ahead earnings changes, Lev and Thiagarajan (1993) support the incremental value-relevance of a set of financial variables over earnings. Abarbanell and Bushee (1997) build upon the findings of Lev and Thiagarajan (1993) and test whether their proposed financial signals are useful in predicting future changes in earnings and revisions in analysts' earnings forecasts. Their findings are consistent with the underlying focus of fundamental analysis on the prediction of earnings and the authors show that fundamental signals which are related to future earnings news provide information about future returns. In line with an errors-in-expectations hypothesis, the abnormal return performance does not persist into the second year of the trading strategy and the generated abnormal returns in the first year are concentrated around quarterly earnings announcements. (Abarbanell and Bushee 1997)

Complementary to their findings concerning the underreaction of investors to fundamental signals, Soliman (2008) points out a market underreaction to the information provided by the components of a DuPont analysis. The author documents that the market recognizes the future RNOA implications of these components and that it responds to changes in ATO consistent with the components' predictive properties. (Soliman 2008) Still, the future return tests show that the response is incomplete as there appears some information in the DuPont components that goes unused by analysts, which reflects itself in the predictability of future forecast errors of analyst estimates. (Soliman 2008) Li et al. (2014) support the conclusion of Soliman (2008) by highlighting the usefulness of a DuPont decomposition in terms of forecasting the variance in future growth rates in operating profits and in forecasting the variance in future stock returns.

However, a main concern regarding the usefulness of a mechanical fundamental analysis in predicting short-term earnings and the cross-section of returns is, that by considering a sufficient number of variables, some of them will generate abnormal returns by mere chance. This tendency is particularly raising concerns as researchers tend to have a high level of discretion in their selection as well as construction of fundamental signals and composite scores. (e.g., Richardson et al. 2010) Yan and Zheng (2017), however, document that fundamental-based signals show strong signs of performance persistence and conclude that the predictive ability of many fundamental signals is unlikely driven by data mining. The authors use a study design based on a contraction of a universe of fundamental signals and apply a bootstrap approach to measure the impact of data mining. In line with prior evidence, abnormal returns of the fundamental-based strategies are concentrated around subsequent earnings announcements, with the return prediction effect being particularly pronounced for small stocks with low-institutional ownership, high-idiosyncratic volatility, and low analyst coverage. (Yan and Zheng 2017) These findings are consistent with behavioural arguments and suggest that the abnormal returns of fundamental-based trading strategies are likely attributable to errors-in-expectations of investors.

2.2 Two-dimensional errors-in-expectations

Given the extensive evidence of literature on behavioural explanations of the value premium and the comprehensive studies on investors' underreaction to fundamental signals, research has commenced to combine these two dimensions. The first notable study that aimed at combining an underreaction to a strength in fundamentals with the value premium was conducted by Piotroski (2000). The author shows that by discriminating between strong and weak companies based on historic financial statement information, the return performance of a B/M strategy can be improved. This differentiation of eventual winners and losers aims at shifting the distribution of the returns earned by the value investor, and does so successfully, particularly in slow information dissemination environments. (Piotroski 2000)

The composite score that the author uses is comprised of fundamental signals that refer to three areas of a firm's financial condition: profitability, financial leverage/liquidity, and operating efficiency. In other words, Piotroski (2000) aims to capture systematic errors in market expectations which express themselves as an underreaction of investors to the strength in fundamentals and as an investors' ignorance of fundamental signals that predict future changes in earnings and revisions in analysts' earnings forecasts. (e.g., Ou and Penman 1989, Lev and Thiagarajan 1993, Sloan 1996, Abarbanell and Bushee 1997) The main concern of a contemporary value investor who aims at capturing growth at a reasonable price and invests for the long run is, however, whether the fundamental strength that Piotroski's (2000) F-Score indicates is of persistent nature. In other words, does this composite meausre add value above and beyond the findings of prior research related to an underreaction of investors to the strength in fundamentals and to errors-in-expectations in general?

Although Piotroski (2000) observes a significant positive relation between F-Score and the one-year-ahead mean ROA, a critical reader might argue that this evidence is by itself insufficient to draw inferences about the persistence of fundamental quality concerning longer time horizons. In fact, this relationship is in line with expectations if a F-Score based strategy proxies for a temporary underreaction to a firm's strength in fundamentals which is corrected as systematic errors in expectations unravel during subsequent earnings announcements. (e.g., La Porta 1996, Dechow and Sloan 1997). Piotroski (2000) even highlights the remarkable consistency with previous findings of La Porta (1996) and points to a potential slow information processing of investors, which is pronounced for small firms with low analyst following and low share turnover. It is a matter of the empirical part of this thesis to provide evidence on the characteristics of a double sorted F-Score and B/M portfolio.

According to prior research, a self-financing portfolio formed on F-Score performs poorly out-of-sample (e.g., Hou et al. 2015, Linnainmaa and Roberts 2018) and its excess returns fail to be significant when using Harvey et al.'s (2016) suggested test statistic cut-off level of 3.0 to account for potential data-snooping bias. Still, this composite measure not only improves the performance of a B/M investment strategy (Piotroski and So 2012), but also the one of a V/P trading strategy as proposed by Frankel and Lee (1998). Frankel and Lee (1998) estimate the fundamental value of a firm by using a residual income model and I/B/E/S consensus earnings forecasts as an input for the model. Their price-scaled fundamental value estimate explains the cross-sectional variation in stock prices and predicts the B/M ratio. Moreover, this measure predicts cross-sectional returns over longer time horizons, thus generating buy-and-hold returns more than twice those from B/M strategies over a two- and three-year holding period. (Frankel and Lee 1998) The authors suspect that frequently used market multiples such as P/B and P/E may work because their accounting component reflects some dimension of the by Frankel and Lee (1998) proposed fundamental value estimate.

Both approaches, the one of Frankel and Lee (1998) and the one of Piotroski (2000), are based on simple fundamental analysis. Hence, to further account for the richness of disaggregated financial statement information, and to improve the return of a V/P strategy which purchases stocks whose prices lag fundamental values, Li and Mohanram (2019) propose to combine the two trading strategies. When both approaches yield high ranks to a stock it is suggestive for an underreaction of investors to a firm's strength in fundamentals which has yet to be reflected by the stock price. While Li and Mohanram (2019) forecast future earnings by using a time series model, which is subject to the criticism that cross-sectional forecasts tend to have higher absolute forecast errors compared to analyst forecasts for the subsample where analyst forecasts are available (Hou et al. 2012), their results are consistent with the one of Frankel and Lee (1998) and deliver valuable incremental insights. Li and Mohanram (2019) demonstrate that F-Score is negatively correlated with V/P and that a portfolio double sorted on the two respective measures generates a significantly higher alpha relative to factor models. However, when considering a bivariate sorted F-Score and V/P portfolio in detail, its monthly returns behave like the ones of junk stocks according to the definition of Asness et al. (2019). Hence, even when using the incremental information provided by F-Score, prior evidence casts doubt on whether this two-dimensional investment strategy is successful in separating long-term winners from long-term losers among value stocks. In fact, it raises the concern that such a portfolio strategy does not capture growth at a reasonable price but rather reflects temporary errors-in-expectations which express themselves as a transient underreaction of investors to a strength in fundamentals that is corrected after subsequent earnings releases.

2.3 Rationalizing the performance of contemporary value investors by using factor models

Despite these concerns about the ability to successfully capture contemporary value investing with formulaic trading strategies, a contemporary value investor might according to the evidence of Asness et al. (2019) still be able to use a formulaic investment approach based on a combination of quality and value to successfully capture firms with persistent quality. In fact, Asness et al. (2019) show that quality is sticky and that high-quality firms selected based on their past profitability, growth, and safety remain high quality firms five- and ten years after portfolio formation. In terms of pricing, the authors demonstrate that firms that are safe, profitable, growing, and well-managed command higher prices on average, yet the price commanded is still too low. Correspondingly, their proposed composite quality factor QMJ (quality-minus-junk) predicts future risk-adjusted returns. In line with the findings of Novy-Marx (2013), both the QMJ and PMU (profitable-minus-unprofitable) portfolios have a negative market, value, and size exposure, while generating positive monthly alpha. When controlling for quality, the value-effect becomes even stronger. (Asness et al. 2019) This finding aligns with the concept of buying quality stocks at a reasonable price and refers back to Graham and Dodd (1934) who emphasize that an investment operation must always consider the price as well as the quality of the security.

Simultaneously, according to Frazzini et al.'s (2013) empirical analysis of Berkshire Hathaway's investment performance, Buffett's success appears to be neither luck nor magic, but is rather attributable to his skills as a capital allocator, the use of leverage, and his portfolio exposure towards safe, cheap, and high-quality stocks. While the standard three- and four-factor models (Fama and French 1993, and Carhart 1997) cannot explain his investment success (Martin and Puthenpurackal 2008, Frazzini et al. 2013), extending the Fama and French (1993) and Carhart (1997) four-factor model by the factors betting-against-beta (BAB) and quality-minus-junk (QMJ) helps explain a large part of his outperformance over the market. (Frazzini et al. 2013, Frazzini and Pederson 2014, Asness et al. 2019) In fact, when considering the returns of Berkshire Hathaway's 13-F portfolio from 1980 to 2011 and when analysing the return performance relative to the extended factor model, Warren Buffett has not generated statistically significant alpha. His 13-F portfolio has a positive loading on MKT, HML, BAB, and QMJ, and has a negative loading on UMD. (Frazzini et al. 2013)

While the rigorous empirical analysis of Frazzini et al. (2013) helps explain Berkshire Hathaway's investment performance, the implications of these findings on market efficiency are less obvious. The provided evidence might still be in line with market efficiency if the documented relation between these quality measures and the ex-post returns is attenuated, noisy, potentially biased, and particularly in the case of QMJ, subject to overfitting bias. Moreover, the QMJ factor might be linked to risk in a way that is not captured by the used safety measure of Asness et al. (2019). Hence, by considering analysts' expectations of the price of quality using the methodology of Brav et al. (2005), the authors test whether the limited explanatory power of quality on price is driven by mispricing. While analysts' target price forecasts are consistent with the concept that high-quality stocks merit higher prices, analysts have lower return expectations for high-quality than for junk stocks, which is inconsistent with the high ex-post realized returns for high-quality stocks. (Asness et al. 2019) This result seems to be driven by analysts' overoptimism regarding junk stocks as the dispersion of analyst forecasts is much higher among junk stocks than it is among high-quality stocks.

2.4 Bringing more discipline to the factor "zoo"

Still, as inferences from back-testing composite signals, including but not limited to QMJ, might be the subject to overfitting bias (e.g., Novy-Marx 2015), this study does not apply composite signals in the stock selection process. Rather it uses them to provide investors with useful information about which anomalies or risk factor exposures their portfolio might capture, potentially rationalizing excess returns which have been hastily attributed to mispricing.

To the same degree, the criticism of Feng et al. (2020) applies, and more discipline has first to be brought to the factor "zoo". (Cochrane 2011) Hundreds of factors have been tried, many of which did not make it to publication. Harvey et al. (2016) therefore suggest that not only most claimed research findings in financial economics are likely false, but also that new factors should pass a higher hurdle, a t-statistic greater than 3.0. Following the criticism of Harvey et al. (2016), Linnainmaa and Roberts (2018) perform an out-of-sample analysis of 36 anomalies and inter alia document premia on the profitability (RMW) and investment factor (CMA) that were neither economically nor statistically significant in a pre-sample period from 1926 to 1969. This emphasizes not only that most anomalies might be a decidedly in-sample phenomenon, but also that the choice of the in-sample start date has a profound effect on the significance of an anomaly. (Linnainmaa and Roberts 2018)

Hou et al. (2020) come to similar conclusions by offering a comprehensive replication of 452 anomalies in accounting and finance. In order to avoid that microcaps drive the results, the authors use NYSE breakpoints and value-weighted returns as an anomaly's portfolio weight on microcaps is considerably lower compared to using NYSE-AMEX-NASDAQ breakpoints and equal-weighted returns (7.4 % vs. 64.2 % in the value versus growth category, respectively). (Hou et al. 2020) As anomalies in microcaps are difficult, if not impossible, to exploit in practice due to transaction costs and short-selling constraints, the use of NYSE breakpoints and value-weighted returns is recommendable not only from the viewpoint of a researcher, but also from the standpoint of a contemporary value investor. (Novy-Marx and Velikov 2016)

Hou et al. (2020) document that when imposing a higher multiple test hurdle with an absolute t-statistic value of 2.78, 82 % of the 452 considered anomalies fail to replicate. Most relevant for this thesis is the finding that the trading strategies of La Porta (1996) concerning analysts' overoptimism about high LTG firms, of Abarbanell and Bushee (1997) concerning fundamental signals, of Piotroski (2000) regarding F-Score, of Richardson et al. (2005) on total accruals, and finally of Fama and French (2015) on operating profitability fail to replicate. While the return on equity measure as proposed by Hou et al. (2015) earns significant high-minus-low decile portfolio returns when rebalancing the portfolio monthly, it fails to earn statistically significantly higher returns when the portfolio is rebalanced semi-annually or annually. Given the long-term investment horizon of contemporary value investors (e.g., Greenwald et al. 2004), findings concerning monthly rebalancing are unlikely to add considerable value to adherents of such a philosophy as they are unlikely to turn over their portfolio every month.

What is particularly relevant for this study, however, is that Sloan's (1996) findings concerning operating accruals and the evidence of Ball et al. (2016) regarding cash-based operating profitability can be replicated by Hou et al. (2020) when using NYSE breakpoints and value-weighted returns. Their findings correspondingly complement the evidence of Ball et al. (2016) and suggest that a cash-based operating profitability variable outperforms measures of profitability that include accruals.

2.5 The profitability premium and its potential sources

Nonetheless, in order to avoid being overly dependent on one profitability or quality factor, this thesis proceeds with a discussion of differences in measures that aim at capturing the profitability premium to get a better sense of underlying factor drivers. Finally, this section will reflect on risk- and behavioural-based explanations of the profitability premium.

A discussion about the profitability premium is necessary since there is a controversial debate on which profitability measure is preferable to use as a factor in asset pricing models. (Fama and French 2015, Hou et al. 2015, and Novy-Marx 2013) For instance, Novy-Marx (2013) shows that gross profitability, measured as revenue minus cost of goods sold relative to assets, not only generates strong average hedge portfolio returns, but also exhibits a far stronger return performance than an earnings measure does. According to Novy-Marx (2013), revenues minus cost of goods sold relative to assets is a preferable proxy for profitability as this measure is cleaner than others. For instance, an earnings-based measure is a potentially polluted indicator of profitability due to differences in the accounting, varying levels of advertising, depreciation and amortization, as well as R&D. While accruals and R&D expenditures have power in predicting returns, gross profitability retains its predictive power for the cross-section of returns after controlling for accruals and R&D. (Novy-Marx 2013)

Furthermore, not only does gross profitability subsume the power of other profitability measures such as earnings to book equity, free cash flow to book equity, and EBITDA-to-assets in predicting returns, but it also subsumes the predictive power of the DuPont components for the cross-section of returns. In fact, Novy-Marx (2013) shows that asset turnover and gross margin, both individually and jointly, lose their power in predicting returns in conjunction with gross profitability. This, however, does not necessarily imply that fundamental signals that predict future profitability and returns might not add incrementally to a gross-profitability-based trading strategy. (e.g., Sloan 1996, Richardson et al. 2005) For instance, following the findings of Novy-Marx (2013), Akbas et al. (2017) provide evidence which suggests that financial analysts underreact to predictive information inherent in the trend in firm profitability. Analysts are shown to adjust their forecasts slowly subsequent to earnings surprises, a pattern well documented by Bradshaw et al. (2002) and Soliman (2008), amongst others.

Meanwhile, Novy-Marx (2014) shows that the returns of portfolios univariate sorted on ROIC and gross profitability are amongst several investigated profitability strategies the strongest negatively related with the returns of traditional value strategies. Hence, Novy-Marx (2014) argues that it is useful to analyse profitability in the context of value as both strategies are highly dissimilar in characteristics and covariances, and yet share much in common philosophy. These findings are particularly relevant for this thesis, as the superiority of the gross profitability measure over return on equity, as defined by Hou et al. (2015), might be inter alia either driven by the measure's subsumption of additional predictive characteristics of individual accounting components or by the measure's ability to capture firms with persistent profitability. This thesis will provide evidence thereon and will complement the findings of Hou et al. (2020) which suggest that the RMW factor, defined as revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expenses, all scaled by book equity, fails to replicate.

While a four-factor model based on a market, an industry-adjusted HML, a momentum, and a gross profitability factor helps explain most earnings related anomalies, a self-financing portfolio formed on F-Score and B/M generates significant abnormal returns relative to a joint gross profitability and value investment strategy. Correspondingly, a zero-cost portfolio double sorted on F-Score as a composite measure and B/M might capture errors-in-expectations which are inter alia associated with the accruals and distress anomaly (Sloan 1996 and Campbell 2008). Hence, this predisposition might contribute to the failure of a four-factor model, which includes gross profitability, to explain such a portfolio strategy's returns. (Novy-Marx 2013) For instance, Desai et al. (2004) show that both the accruals and value anomaly are related to investors' errors-in-expectations about a firm's future earnings. Their evidence is most consistent with an overreaction to past accounting data as investors appear to naively extrapolate accounting fundamentals in both cases. (Desai et al. 2004)

This also aligns with the findings of Ball et al. (2016) which suggest that cash-based operating profitability outperforms gross profitability and subsumes the power of accruals in predicting returns. Accordingly, the accruals anomaly strengthens when using a factor model which includes an accruals-based profitability measure. (e.g., Fama and French 2016) Ball et al. (2016) attribute this finding to the observation that accruals allow the regression to extract the cash-based component from the accruals-based profitability variable. Moreover, they show that while accruals predict returns only one year ahead, their proposed operating profitability and cash-based operating profitability measure predict returns persistently over a ten-year investment horizon. (Ball et al. 2016) The persistence in return performance points to a persistence in fundamental quality rather than to short-term errors-in-expectations of investors as indicated by Sloan (1996). While no explicit evidence is offered thereon by Ball et al. (2016), Novy-Marx (2013) shows that current gross profitability has power in predicting long-term growth in profits, free cash flows, and payouts. In return, as gross profitability is strongly related to contemporaneous valuation ratios and to variables that are successfully forecasting gross profit growth, gross profitability can be expected to predict future valuations and, thus, returns. (Novy-Marx 2013)

One question that remains, however, is why the profitability premium exists at the first place, given that the results are difficult to reconcile based on the explanations of the value premium as profitable firms are inter alia less subject to financial distress. (Novy-Marx 2013) Following the findings of Fama and French (2006), Novy-Marx (2013), and Hou et al. (2015), the profitability factor has attracted considerable interest among researchers and has led to both rational and behavioural-based explanations. For instance, Fama and French (2006, 2015) suggest that the profitability effect is consistent with valuation theory, as in a dividend discount model, higher expected earnings are associated with higher expected returns when controlling for B/M and expected investment. (e.g., Sun et al. 2014) Still, the expected earnings used in their model can be either based on rational or irrational investor beliefs.

In line with rational beliefs, Hou et al. (2015) propose a five-factor model similar to the one of Fama and French (2015). The authors argue based on q-theory of investment that given a certain level of investment to assets, firms with a higher level of expected profitability should earn higher expected returns. (Hou et al. 2015) In return, high expected profitability relative to low investment must imply high discount rates, as according to q-theory, a stock's expected return should equal the expected marginal benefit of investment in the future divided by the marginal cost of investment today. (Hou et al. 2015 and Sun et al. 2014) According to Li and Zhang (2010), the marginal cost of investment increases with investment frictions in a q-theory-based framework, and the positive relation between profitability and returns should be stronger for firms which face a low level of investment frictions. Complementary to the findings of Hou et al. (2015), Sun et al. (2014) document a stronger positive effect of gross profitability on returns in countries with low investment frictions, which is according to their conclusion consistent with investment-based asset pricing theory.

Simultaneously, excess returns attributed to profitability might be to a certain degree driven by operating leverage as Kisser (2014) shows that high profitability firms have fixed costs that persistently exceed those of low profitability firms. However, this finding seems to be strongly sensitive to the definition of operating leverage. When following the definition of operating leverage as operating costs scaled by total assets according to Novy-Marx (2011), instead of fixed costs scaled by total assets according to Kisser (2014), profitable firms are reported to have lower levels of operating leverage. (Novy-Marx 2013)

Meanwhile, Wang and Yu (2013) offer a comprehensive evaluation of both risk-based and behavioural-based explanations of the ROE premium according to the definition of Hou et al. (2015). While the authors fail to show that traditional macro variables have predictive power whatsoever the ROE premium, suggesting that risk might only play a marginal role in explaining the factor’s returns, they demonstrate that the ROE premium is particularly pronounced for firms that experience a higher level of information uncertainty. In fact, their findings appear consistent with a behavioural-based explanation. More specifically, in line with the investor inattention hypothesis of Hong and Stein (1999), Wang and Yu (2013) provide evidence in accordance with an ex-ante inattention-induced underreaction.

While these findings are compelling, the evidence of Ball et al. (2016), which suggests that operating profitability predicts returns as far as ten years into the future, is in conflict with such an explanation. If anything, it rather points to an underreaction of investors to cash flow information that is gradually corrected over time. Complementary, Bouchoud et al. (2019) indicate that even though the profitability anomaly is stronger among firms with persistent profitability, this finding is not necessarily in conflict with behavioural-based explanations. While analysts seem to overreact to firms for which they project a high long-term earnings growth rate (Bordalo et al. 2019), investors form their future profit expectations according to the findings of Bouchoud et al. (2019) based on sticky belief dynamics and correspondingly update their beliefs too slowly.

Most recently, Kyosev et al. (2020) provide a comprehensive study on various quality factors, including gross- and cash-based operating profitability, and conclude that the power of these measures in predicting returns originates from their ability to capture future earnings growth. In line with their findings, Erhard and Sloan (2020) emphasize that the profitability anomaly is concentrated among high growth firms, while being absent among low growth firms. According to the authors this relation arises because analysts value stocks by applying similar valuation multiples to firms with similar growth potential. While profitable firms are capable of funding growth internally, unprofitable firms fail to do so and must issues new shares to attain the desired growth, ultimately resulting in the dilution of shareholders. (Erhard and Sloan 2020)

2.6 Connections with the study at hand and research design

Based on these findings of prior research, this study aims to identify bivariate sorted profitability and value portfolio strategies that align the investment principles of contemporary value investors. Hence, a corresponding portfolio strategy should generate abnormal returns relative to the considered factor models and should be composed of firms that exhibit strong profitability characteristics, including a persistence therein in the long run. Correspondingly, the rest of this thesis is organized as follows. Section 3 presents the data sample and according descriptive summary statistics of the variables of interest in this study. These summary statistics are relevant to fully comprehend the results in section 4.1, in which multivariate Fama and MacBeth (1973) regressions on various profitability and value measures are performed. The aim is to critically reflect on potential differences in information content among the considered profitability and value measures. For instance, this study analyses whether a cash-based operating profitability measure not only subsumes the power of accruals, but also the one of gross- and operating profitability in predicting the cross-section of average returns. Subsequently, enterprise value will be used as a conceptually and fundamentally different deflator for cash-based operating profitability to test in how far this alternative value measure has similar desirable profitability and return prediction characteristics as the presented cash-based operating profitability measure.

As this study aims to identify two-dimensional profitability- and value-sorted investment strategies that align the investment principles of contemporary value investors, section 4.2 is concerned with monthly return correlations among the univariate sorted portfolios that are formed on either profitability or value. Subsequently, the return performance and factor exposures of univariate and double sorted portfolio strategies are investigated in detail. While it is crucial to determine which of the investment strategies generate significant alpha relative to the others in the context of zero-cost portfolios, the central interest of this thesis is to empirically explore whether the corresponding long-only portfolios align the investment principles of contemporary value investors. This inter alia comprises strong profitability characteristics among portfolio firms. Section 5, therefore, analyses whether profitability is sticky by testing whether value stocks that were profitable in the past display this characteristic in the future. Complementary, by using Fama and MacBeth (1973) regressions, this study will provide evidence on whether current profitability measures have power in predicting short- to long-term growth across three considered profitability dimensions for value firms.

3 Data sample

This study obtains the monthly stock returns from CRSP and the accounting data from Compustat. Consistent with prior research (e.g., Novy-Marx 2013), the data sample of this study starts one year after the inclusion of AMEX common stocks in the CRSP database and covers

July 1963 to November 2019. The accounting data from Compustat starts in 1961 as annual accounting information is lagged by six months to avoid look-ahead bias (Banz and Breen 1986) and as this study uses lagged deflators for the profitability variables. Following Ball et al. (2016), amongst others, this thesis starts out with a sample of US firms traded on NYSE, AMEX, and NASDAQ, while excluding securities other than ordinary common shares. (CRSP shrcd equal to 10 and 11) Moreover, common shares with a one-digit SIC code of six (financials) are excluded too, as the high leverage applied by financials has different implications as for non-financial firms. (Fama and French 1992) The final sample consists of firms that have non-missing returns, book value of assets, book-to-market, and gross profits.

Following the findings of Shumway (1997) and Beaver et al. (2007) concerning the importance of including delisting firms when testing market efficiency, this study uses CRSP delisting returns, if available, and imputes a return of -30 % when the delisting is performance-related and the delisting return is missing in the CRSP database. While there are many stocks found to delist for liquidation and that do not have delisting returns, almost all of these liquidations had been already announced before the delisting. The corresponding return reaction almost entirely took place around the announcement day. (Shumway 1997)

When it comes to the analysis of investment strategies, portfolios will be value-weighted and formed using NYSE breakpoints. Univariate sorts based on profitability and value measures are used to construct quintile portfolios, while double sorts based on profitability and value are used to construct 25 portfolios (5x5). This study employs unconditional double sorts, which implies that the order of the sort does not matter as portfolios are rather sorted independently into quintiles. The double sorting procedure is correspondingly based on the intersection between the univariate sorted quintile portfolios. The required factor return data to determine the factor exposures of the considered investment strategies are obtained from the website of Kenneth R. French and AQR, while the 30-day US Treasury bill rate is used as a risk-free rate and obtained from CRSP. Variable definitions, including the calculation of accounting measures, are explained in detail in the Appendix.

3.1 Empirical methodology

Before the results of this study are presented, it is vital to critically reflect on choices in empirical methodology and on its consequences on potential biases in research. For instance, this study strictly accounts for publication bias by putting restrictions in place that, if anything, weaken the results of the tested hypotheses. The choices that have been made are as follows.

First, portfolios are formed using NYSE breakpoints and value-weighted returns as anomalies in microcaps are difficult to exploit in practice due to high transaction costs (e.g., Novy-Marx and Velikov 2016) and as microcaps account for 60 % of the total number of stocks of the NYSE-AMEX-NASDAQ universe, while representing a mere 3 % of aggregate market capitalization. (Fama and French 2008) Second, this study uses annual- rather than monthly-rebalancing as contemporary value investors are unlikely to rebalance their portfolio on a monthly basis. Using monthly rebalancing, however, is found to lead to a stronger monthly return performance for value strategies (e.g., Hou et al. 2020). Third, quintiles are used instead of deciles to ensure that following an unconditional double sort, a sufficient number of stocks is represented in each portfolio. Thereby, this study aims to avoid that the return performance of the portfolios is driven by a small subset of stocks.

Finally, and most importantly, this study sticks to lagged assets and lagged capital employed as the two main deflators for the profitability variables since the profits of a given fiscal year can be largely attributed to the assets and the capital employed that were already in place at the beginning of the year rather than at the end of the year. Following the reasoning of Hou et al. (2020), the assets at the end of the year reflect an accumulation of investment over the current period and relate to future rather than current profits. Using lagged assets should be considered a particular conservative choice as it is shown by prior research (e.g., Hou et al. 2020) to lead to lower zero-cost portfolio excess returns for various profitability measures, including but not limited to gross- and operating profitability. Hou et al. (2020) suspect that the gross profitability premium is confounded with the investment premium when using contemporaneous assets as a deflator for gross profitability since gross profitability to assets equals gross profitability to lagged assets divided by asset growth. An analysis that critically reflects on deflator choice is presented as a robustness test in the Appendix.

Yet another concern that this study has to address is look-ahead bias. Compared to most prior studies in finance research which assume that the accounting information is publicly available by the end of June in the calendar year following the fiscal year with which the accounting information is associated (e.g., Fama and French 1992, Novy-Marx 2013), this thesis lags the closing date of the accounting year by six months. This small difference has a profound impact on a study’s exposure to look-ahead bias as several firms, including but not limited to General Mills, Nike, and Paychex, have May as a closing date of the accounting year and as Compustat misleadingly reports their fiscal year$_{t}$ as fiscal year$_{t-1}$. For instance, for fiscal year 2019, Paychex’s closing date of the accounting year was 31st May 2019 and its fiscal year 2019 is misleadingly reported as fiscal year 2018 by Compustat. Hence, in the case of Paychex, this study correspondingly assumes that the accounting information is publicly available by November 2019. Meanwhile, prior research would assume that it is available by June 2019 as the calendar year following the fiscal year 2018 is 2019 and when additionally lagging the accounting information by six months, the earnings results are expected to be publicly available by June 2019. However, Paychex's fourth quarter earnings of fiscal year 2019 were only reported in July 2019 and a study which assumes that the annual accounting information is publicly available by the end of June in the calendar year following the fiscal year with which the accounting information is associated is correspondingly exposed to look-ahead bias.

While lagging the closing date of the accounting year by six months can be considered as a too conservative choice since firms are required to file their 10-K reports with the SEC within 90 days of their fiscal yearend, almost 40 % of the December fiscal yearend firms were unable to comply with the 90-day rule according to the findings of Alford et al. (1992). Therefore, using a lag of six months is a common practice among researchers. (e.g., Fama and French 1992, Ball et al. 2016)

3.2 Descriptive statistics of the variables of interest

The variables of interest of this study that are used in subsequent regression analysis and for portfolio sorts are reported with summary descriptive statistics and with the time-series averages of the monthly Spearman rank correlations in Table 1 and Table 2, respectively. This section should provide first indications on whether there are differences in information content among the considered profitability and value measures. In order to account for potential disparities in information content among value measures, enterprise-value-deflated operating income and enterprise-value-deflated cash-based operating profitability are used to move beyond the traditional definition of value investing as book-to-market investing. Likewise, lagged-assets-deflated gross-, operating-, and cash-based operating profitability are the main variables employed to account for the profitability dimension. While this study complementary uses contemporaneous assets and lagged capital employed as alternative deflators for the considered profitability measures, the corresponding results hereof are reported as a robustness check in the Appendix.

First, when considering the profitability dimension, the lagged-assets-deflated profitability measures have distributions that resemble the ones reported by prior research. (e.g., Ball et al. 2016) For instance, the average annual gross profitability is approximately 41.6 % of lagged assets and the average annual operating- and cash-based operating profitability of lagged assets amounts to 14.6 % and 12.1 %, respectively. All deflated profitability measures are positively correlated which indicates that there is a substantial common component to these variables. While F-Score as a composite profitability measure has the weakest correlations with the other considered profitability metrics, high F-Score firms still exhibit desirable characteristics. These firms are associated with an on average higher operating- and cash-based operating profitability as well as with lower valuation ratios. Similarly, the strength of association between gross profitability and cash-based operating profitability is only moderate too. (ρ=0.41).

Meanwhile, the considered operating profitability metrics are highly positively correlated with each other. For instance, the strong correlation among operating profitability and cash-based operating profitability (ρ=0.76) may lead to problems in subsequent regression specifications as the effect of each regressor on the dependent variable might be difficult to distinguish when including both measures as independent variables in a regression. (e.g., Bali et al. 2016) However, while operating profitability is positively related to accruals (ρ=0.24), after removing the accruals component from operating profitability, cash-based operating profitability and accruals are negatively correlated (ρ=-0.15). In line with the evidence of Ball et al. (2016), the negative correlation indicates that firms that have a high level of accruals tend to be less profitable on a cash-basis, and yet have an on average higher level of gross- and operating profitability. Moreover, the moderate positive correlation among the operating profitability measures and size suggests that an investment strategy based on high operating profitability is likely to tilt towards large stocks. For gross profitability, on the other hand, the correlation with size is weakly negative. Collectively, these findings suggest that a variation in profitability measures for portfolio sorts is expected to lead to noticeable differences among profitability portfolios when it comes to their respective firm characteristics, average monthly excess returns, and risk factor exposures. The following sections of this thesis will provide evidence for this hypothesis.

Meanwhile, when accounting for the value dimension, all considered profitability measures are negatively correlated with book-to-market, implying that portfolios formed on the basis of profitability are likely to be growth strategies. In other words, high B/M firms are associated with a lower level of profitability, being in line with evidence of prior research. (e.g., Novy-Marx 2013) On the other hand, enterprise-value-deflated cash-based operating profitability and enterprise-valued-deflated operating income are positively correlated with all deflated profitability measures which suggests that a stock selection based on both valuation ratios predisposes investors to companies with an on average higher level of profitability. The correlation is the strongest between cash-based operating profitability scaled by enterprise value and cash-based operating profitability scaled by lagged assets (ρ=0.61), whereas its correlation with B/M is only moderate (ρ=0.38). Collectively, these findings imply that even without accounting for the profitability dimension explicitly, the right valuation ratio choice can prevent the investor from a portfolio tilt towards unprofitable firms. Whether a variation in the valuation measure used is affecting its predictive power for the one-month ahead returns, and whether it predisposes a portfolio manager to invest in firms with temporarily inflated accounting numbers, will be investigated in detail in the upcoming sections of this thesis.

4 The cross-section of returns

4.1 Fama and MacBeth (1973) regressions

Hence, this section presents cross-sectional regressions of monthly returns on profitability and value measures to get a better understanding of how these variables relate to future stock returns. Following the conclusion of Ball et al. (2015) that gross profits, net income, and operating profits have the strongest predictive power for the monthly cross-section of returns when using book value of assets as a deflator for the profitability variables, this study incrementally adds to their findings by including cash-based operating profitability as an alternative profitability measure and lagged capital employed as a novel deflator choice. Hence, to compare the explanatory power of gross-, operating-, and cash-based operating profits for the cross-section of returns in this study, book value of assets, lagged book value of assets, and lagged capital employed are used as deflators. Consistent with the findings of Hou et al. (2020), all considered profitability measures have the strongest predictive power for expected monthly returns when scaled by contemporaneous assets. The results on a variation in deflator choice as well as its implications on future research are presented in detail in the Appendix as this section rather aims to incrementally add to the understanding of fundamental differences among the considered profitability and value measures. Accordingly, lagged assets will be consistently used as a deflator for profitability in the subsequent analyses.

Following Novy-Marx (2013), the natural logarithm of B/M, the natural logarithm of market capitalization, and the prior month as well as prior 12-month period excluding month t-1 returns are used as control variables in cross-sectional regressions of monthly returns. As extreme data points of the considered independent variables are assumed to indicate the true values of a given variable, these data points are not trimmed but winsorized at the 1% and 99% levels in order to avoid that they exert an undue influence on the regression results. In line with Ball et al. (2015), microcaps, being defined as stocks with a market value of equity below the 20th percentile of the NYSE market capitalization distribution, are excluded from this analysis. As annual accounting data is used, the according information is lagged for the subsequent twelve months to have consecutive time series of observations. Table 3-5 present average Fama and MacBeth (1973) regression slopes which can be interpreted as monthly returns of a zero-cost portfolio that trades on the part of the variation in each explanatory variable that is orthogonal to every other independent variable. (e.g., Ball et al. 2016)

4.1.1. Profitability measures

More specifically, the profitability dimension is presented first, and Table 3 correspondingly reports the regressions of monthly expected returns on the considered profitability measures. The coefficients in the regression specifications (1)-(3) imply that a one percentage point increase in gross profits to lagged assets is ceteris paribus associated with a 0.004 percentage point increase in monthly returns, while the effect increases to 0.014 percentage points for operating profitability to lagged assets and to 0.018 percentage points for cash-based operating profitability to lagged assets. As the comparison between the measures might be hard to comprehend because of the diverging scale and variances of the considered independent variables, the effect of a one-standard deviation change in the regressors for expected monthly returns is assessed. For instance, a one-standard deviation change in gross profitability to lagged assets is ceteris paribus associated with an increase in expected monthly returns of 0.12 percentage points, while for operating- and cash-based operating profitability a one-standard deviation change is ceteris paribus associated with a difference in future monthly stock returns of 0.25 and 0.34 percentage points, respectively. Irrespective of which profitability measure is considered, each of them has an economically and at a 1 % significance level statistically significant power in predicting returns.

Still, as extensively discussed in the literature review of this thesis, an investor might be concerned that the power of these profitability measures in predicting returns might be driven by an already well-documented anomaly such as the accruals anomaly. Hence, there might be pronounced differences among the profitability measures' predictive power for the cross-section of returns after controlling for accruals. First, consistent with the findings of Ball et al. (2016), regression (1) in Table 4 shows that accruals are an economically and at a 1 % significance level statistically significant negative predictor of expected monthly stock returns. Second, as opposed to initial concerns, the regressions (2)-(3) of Table 4 indicate that the predictive power of gross profitability and operating profitability even slightly increase when controlling for accruals. Collectively with the observed moderately positive correlation among the two profitability measures and accruals, the evidence suggests that gross profitability and operating profitability capture an accrual component that investors apparently fail to distinguish from a more persistent cash flow component, being in line with the conclusion of Sloan (1996) that investors behave as if accruals and cash flows are equally persistent.

This inference, however, is challenged by the regression (4) in Table 4 which includes cash-based operating profitability together with accruals and the outlined controls as explanatory variables. According to the regression results, cash-based operating profitability not only maintains its predictive power for expected monthly returns when controlling for accruals, but it also subsumes the predictive power of accruals for the cross-section of returns as the regression coefficient on accruals becomes statistically indistinguishable from zero (t=-0.74). The latter observation is inconsistent with the hypothesis of Sloan (1996) that investors fail to distinguish an accrual from a more persistent cash flow component. Instead, in line with the findings of Ball et al. (2016), this evidence is collectively suggesting that accruals allow the regression to extract the cash-based component from the accruals-based profitability variable. Consistent with their hypothesis that accruals predict returns due to their negative correlation with the cash component of operating profitability, the slope coefficients on accruals and operating profitability in regression (3) of Table 4 are additive inverses. In other words, accruals have predictive power for expected returns largely because high-accrual firms tend to have an on average lower cash-based profitability.

The regressions (5)-(7) in Table 4 further underline these findings by showing that cash-based operating profitability wins the horse race among the considered profitability metrics. This accounting measure not only subsumes the power of accruals in predicting monthly returns, but it also subsumes the one of gross- and operating profitability, individually and collectively. Compared to the findings of Ball et al. (2016), operating profitability lost all its economically and statistically significant power in predicting returns. In other words, cash-based operating profitability, a measure devoid of accounting accruals adjustments, dominates accruals-based profitability measures in predicting the cross-section of returns.

The aim of the upcoming section is to move beyond the profitability dimension and to present an enterprise multiple on the basis of cash-based operating profitability. Hence, enterprise value will be used as a conceptually and fundamentally different deflator for this accounting variable to test in how far this alternative value measure has similar desirable profitability and return prediction characteristics as the presented cash-based operating profitability measure.

4.1.2. Valuation measures

While various profitability measures have been already extensively studied by research to come up with a proxy for the profitability premium, much less consideration has been devoted to valuation ratio choice. Following the findings of Fama and French (1993), which suggest that size and B/M absorb the apparent roles of E/P and leverage in average returns, B/M has been almost exclusively used as a valuation measure in the belief that different price ratios are just different ways to scale a stock's price with a fundamental. Not the least because of the so far narrow definition of the value dimension does this thesis use book-to-market and enterprise multiples based on operating income and cash-based operating profitability as alternative valuation measures. Table 5 reports the corresponding Fama and MacBeth (1973) regression results. The regressions in column (1)-(4) not only show that all chosen valuation measures have strong positive predictive power for expected monthly returns, but they also highlight that the information content of the considered value measures is not the same. Comparable to the horse race among the considered profitability variables, enterprise-value-deflated cash-based operating profitability subsumes most of the power of the other two valuation measures in predicting the cross-section of returns. The regression coefficients of the two value measures are both no longer statistically significant at a 5 % significance level after controlling for enterprise-value-deflated cash-based operating profitability.

In order to better understand what information content the different price and enterprise value ratios might capture, on earlier findings of this study has to be reflected on first. While B/M is negatively correlated with all considered profitability measures, enterprise-value-deflated operating income and enterprise-value deflated cash-based operating profits are moderately positively correlated with all profitability variables. In other words, when not explicitly controlling for profitability in the regressions, the considered enterprise multiples presumably partly capture the omitted profitability measures' predictive power for monthly returns.

Still, this interpretation does not account for why enterprise-value-deflated cash-based operating profitability is subsuming the power of enterprise-value-deflated operating income in predicting monthly returns. Nonetheless, while enterprise-value-deflated operating income is positively correlated with accruals (ρ=0.22), a higher value of enterprise-value-deflated cash-based operating profitability tends to be associated with an on average lower level of accruals (ρ=-0.29). Hence, the ability of enterprise-value-deflated cash-based operating profitability to subsume the power of enterprise-value-deflated operating income in predicting monthly returns might be once again attributable to the former measure being devoid of accounting accrual adjustments. In fact, as the regression results in column (5)-(6) of Table 5 illustrate, cash-based operating profitability scaled by enterprise value subsumes the power of accruals in predicting returns. Meanwhile, controlling for accruals does not affect the predictive power of enterprise-value-deflated operating income, nor does this measure subsume the predictive power of accruals to any extent. If anything, the predictive power of accruals for the cross-section of returns becomes stronger when using enterprise-value-deflated operating income instead of B/M as a value measure in the regression. Hence, complementary to prior observations, this evidence is further supporting the supposition of Ball et al. (2016) that accruals allow the regression to extract the cash-based component from the accruals-based profitability variable. This effect appears to be so strong as to reflect itself even when using conceptually and fundamentally different deflators.

The multivariate Fama and MacBeth (1973) regression summarized in column (7) of Table 5 further challenges the stream of prior research which considers different price ratios as just different ways to scale a stock's price with a fundamental. In fact, when additionally including the previously considered profitability measures in a multivariate Fama and MacBeth (1973) regression, enterprise-value-deflated cash-based operating profitability loses its predictive power for expected monthly returns, while the coefficient on B/M regains economic and statistical significance at a 1 % significance level. Collectively with the prior observation that cash-based operating profitability scaled by lagged assets and cash-based operating profitability scaled by enterprise value are strongly positively correlated (ρ=0.61), the evidence rather suggests that a profitability and a value measure share a substantial common component. Although lagged-assets-deflated cash-based operating profitability subsumes together with B/M the predictive power of enterprise-value-deflated cash-based operating profitability for the cross-section of returns, a conclusion that the latter variable is not a useful measure for portfolio sorts would be prematurely drawn as will be shown in the course of this thesis. If anything, cash-based operating profitability is consistently found to have a strong power in predicting the cross-section of returns, even when using with enterprise value a conceptually and fundamentally different deflator.

Although the evidence gathered based on the previous regressions appears conclusive, it is important to reflect on general methodological weaknesses of Fama and MacBeth (1973) regressions. While the independent variables in all of the previously considered regressions have been winsorized at the 1 % and 99% levels, and stocks with a market value of equity below the 20th percentile of the NYSE market cap distribution have been excluded from the analysis, skewed distributions of the considered measures might still drive the regression results.

Moreover, as the Spearman rank correlations between the considered explanatory variables and the expected monthly returns tend to be consistently larger in magnitude than their Pearson product-moment correlations (not reported), the relationship among the variables is monotonic, but not necessarily linear. Although the two types of correlation have the same sign for all considered profitability and value measures, using regression techniques might in the case of non-linearity still lead to diverging results from portfolio sorts. (e.g., Bali et al. 2016) Due to these concerns, the following section performs return tests based on zero-cost and long-only quintile portfolios that are annually rebalanced at the end of June.

4.2 Univariate and bivariate portfolio sorts

4.2.1. Portfolio returns and return correlations

First, in order to test whether the previous findings can be replicated using portfolio sorts, the average zero-cost portfolio returns of the outlined profitability and value investment strategies are compared and presented in Panel A of Table 6. For instance, a self-financing portfolio formed on lagged-assets-deflated gross profitability earns monthly excess returns of 0.24 % and correspondingly has weaker predictive power for the cross-section of returns as initially reported by Novy-Marx (2013) who uses contemporaneous assets and decile portfolios. Moreover, the findings of prior research on the return performance of a zero-cost portfolio sorted on operating profitability cannot be replicated as this anomaly cannot clear the single test hurdle of $|t| \geq 1.96$ in this study. While comparability is constrained due to the use of quintile instead of decile portfolios, this return anomaly also fails to clear the same single test hurdle in the study of Hou et al. (2020) when using decile portfolios.

However, consistent with the previously presented regression results, a high-minus-low portfolio sorted on lagged-assets-deflated cash-based operating profitability generates economically significant monthly excess returns of 0.35 % that clear the multiple test hurdle of $t= 3.0$ as suggested by Harvey et al. (2016). Moreover, despite the by previous research (e.g., Linnainmaa and Roberts 2018, Hou et al. 2020) reported poor post-sample performance of Piotroski's (2000) F-Score, the composite anomaly can clear the multiple test hurdle of $t=3.0$ with average monthly excess returns of 45 basis points in this study.

Meanwhile, all considered value measures clear the single test hurdle of $|t| \geq 1.96$. However, there is a strong divergence in return performance. The average monthly excess returns of a self-financing portfolio sorted on enterprise-value-deflated cash-based operating profitability of 0.63 % are almost twice as large as the 0.33 % monthly excess returns of a high-minus-low book-to-market-sorted portfolio. Hence, in line with prior regression results, using enterprise multiples strengthens the predictive power of value for the cross-section of returns.

Still, as the principal aim of this thesis is not to investigate profitability and value portfolio strategies in isolation, monthly return correlations are considered and presented in Panel B of Table 6 to reflect on two-dimensional sorted portfolio choice. This is particularly important as some of the considered measures, including but not limited to cash-based operating profitability scaled by lagged assets and cash-based operating profitability scaled by enterprise value, have been shown to capture a similar information content in the previous section of this study. In other words, a double sort based on a profitability and value measure that capture similar effects and whose univariate sorted portfolios yield similar returns might add little value above and beyond the individual strategies in isolation.

On the other hand, and in line with the findings of Novy-Marx (2014), the monthly returns of a high-minus-low gross-profitability-sorted portfolio are highly negatively correlated with the monthly returns of a zero-cost portfolio sorted on B/M (ρ=-0.66). At large, the monthly return correlations among profitability- and value-sorted portfolios are consistently negative when using B/M as a value measure. As a result, a double sort appears to be particularly attractive for traditional value investors as profitability is likely to provide a valuable hedge to traditional value.

Similarly, the correlation between the monthly returns of a self-financing portfolio formed on gross profitability and one formed on enterprise-value-deflated cash-based operating profitability is moderately negative too (ρ=-0.31). This correlation is surprising, given that the latter value measure has been shown in a prior section of this study to predispose investors to firms with an on average higher profitability across all considered profitability dimensions. Likewise, the monthly return correlation between a self-financing portfolio formed on the basis of cash-based operating profitability scaled by lagged assets and one based on cash-based operating profitability scaled by enterprise value is only weakly positive (ρ=0.13) despite the previously documented strong Spearman rank correlation (ρ=0.61). When using lagged capital employed as a deflator for cash-based operating profitability, the monthly return correlation with the same valuation measure even turns weakly negative (ρ=-0.05). In other words, a given profitability measure is likely not only enhancing the performance of a B/M strategy, but also the one of an enterprise-multiple-based portfolio strategy which already predisposes investors to firms with on average desirable profitability characteristics.

In fact, Panel A of Table 7 shows that all considered self-financing portfolios double sorted on profitability and value generate average monthly excess returns which clear the multiple test hurdle of t=3.0 and which are higher than the ones of each univariate sorted high-minus-low portfolio. The highest respective monthly excess returns are generated by a self-financing portfolio formed on the basis of lagged-assets-deflated operating profitability and B/M, as well as by a zero-cost portfolio sorted on lagged-assets-deflated cash-based operating profitability and B/M. This finding aligns with the observed strong negative monthly return correlations among the univariate sorted portfolios and with the presented Fama and MacBeth (1973) regression results. Still, unconstrained investors who consider implementing a self-financing portfolio formed on profitability and value are less concerned about monthly excess returns than they are about multi-factor model alphas, as the factors and the risk-free rate can be used to create a mean-variance efficient portfolio. (e.g., Ball et al. 2015) Hence, it is essential to reflect on factor model alphas and factor exposures of these portfolio strategies in the next section of this study. As will be shown in the course of this thesis, monthly excess returns based on annual portfolio rebalancing are neither for long-only contemporary value investors the major determinant in their investment selection process.

4.2.2. Factor regressions and potential risk factor exposures

Correspondingly, this section reports the results of the factor regressions of the univariate and double sorted portfolios to reflect on monthly factor model alphas and potential risk factor exposures. When considering the univariate sorted self-financing portfolio strategies first, which are presented in Panel A of Table 8, all high-minus-low profitability-sorted portfolios capture firms which resemble growth stocks in terms of both characteristics and covariances. Moreover, these profitability-sorted portfolios also have similar factor loadings beyond the HML factor in a Fama and French (2015) five-factor and a by BAB and QMJ extended Fama and French (1993) and Carhart (1997) four-factor regression. Still, a notable difference is that the monthly returns of a portfolio sorted on gross profitability behave like the ones of small stocks, while the monthly returns of a portfolio formed on the basis of operating profitability behave like the ones of large stocks, which is consistent with the Spearman variable rank correlations presented in a prior section of this study. While all three self-financing profitability-sorted portfolios generate an economically and at a 1 % significance level statistically significant monthly alpha relative to the Fama and French (2015) five-factor model, they fail to generate abnormal monthly returns relative to the alternative factor model specification.

Similarly, when comparing the return characteristics of a zero-cost portfolio formed on B/M and one sorted on enterprise-value-deflated cash-based operating profitability, the discussion about fundamental differences among the considered value measures intensifies. In line with prior observations, a self-financing portfolio formed on the basis of enterprise-value-deflated cash-based operating profitability not only tilts towards firms whose characteristics resemble the ones of highly profitable firms, but also its monthly returns behave like the ones of firms with robust profitability and high quality. The loading of the portfolio on SMB is not statistically significant and the self-financing portfolio generates an economically and statistically significant monthly alpha above and beyond the desirable factor loadings in both factor regressions.

On the other hand, a high-minus-low book-to-market-sorted portfolio loads positively on SMB, has a loading on RMW which is not statistically significant at a 5 % significance level, and its monthly returns behave like the ones of junk stocks when considering a by BAB and QMJ extended Fama and French (1993) and Carhart (1997) four-factor regression. Largely due to the amplified loading of the zero-cost book-to-market-sorted portfolio on the HML factor, both factor models do not face difficulties in pricing this trading strategy. Hence, these findings complement previously presented Fama and MacBeth (1973) regressions which suggest that enterprise-value-deflated cash-based operating profitability captures information beyond the one of book-to-market that is relevant in asset pricing. Correspondingly, the performance of the considered factor models in pricing value investment strategies strongly depends on how value is defined.

It is particularly the double sorted profitability and value portfolio strategies which plague the factor models, and among which the fundamental differences of the considered valuation measures are specifically pronounced. For instance, value measure choice apparently dominates when using double sorts. Panel B of Table 8 provides further evidence thereon by showing that factor loadings are remarkably similar when using varying profitability metrics but the same value measure for double sorts. Collectively with the prior observation that the monthly returns of the zero-cost portfolios formed on profitability and B/M are only weakly positively correlated with the ones that use an enterprise multiple for two-dimensional portfolio sorts, the evidence suggests that the variation in information content among value measures is stronger than it is among profitability measures. In order to further enhance the understanding of divergences in return performance among these trading strategies, this study investigates whether the monthly alpha and the factor exposures of the double sorted zero-cost portfolios are either predominantly driven by the long- or short-side of the trading strategy. This is highly relevant for the implementation of the investment strategies as investors may face challenges in executing a portfolio strategy whose returns are almost exclusively driven by the short side. For instance, arbitrage risk and short-sale constraints may impose severe restrictions to investors. Correspondingly, Panel C and Panel D of Table 8 present the factor regressions of long-only and short-only profitability- and value-sorted portfolios, respectively.

When considering the self-financing portfolios double sorted on profitability and enterprise-value-deflated cash-based operating profitability, both the highest and lowest quintile portfolios generate economically and statistically significant monthly excess returns that remain unexplained by the Fama and French (2015) five-factor model. Accordingly, the monthly excess return performance of self-financing portfolios double sorted on profitability and enterprise-value-deflated cash-based operating profitability is neither exclusively driven by the highest nor the lowest quintile portfolios. Overall, the monthly returns of the corresponding double sorted zero-cost portfolios behave like the ones of profitable firms that invest conservatively.

While these portfolios appear to generate growth-like returns according to the Fama and French (2015) five-factor regression, the loading on HML turns positive when considering a by BAB and QMJ extended Fama and French (1993) and Carhart (1997) four-factor regression. When taking the strong positive MOM and QMJ loadings that these zero-cost portfolios have in the extended factor regression into account, the evidence collectively suggests that when not explicitly controlling for MOM and QMJ, HML partly captures effects that these factors aim to proxy for. As a result, due to the problems that the Fama and French (2015) five-factor model faces in pricing these portfolios strategies, the monthly generated alpha is for all of the zero-cost portfolios formed on the basis of profitability and enterprise-value-deflated cash-based operating profitability of particularly pronounced economic and statistical significance. In the alternative multifactor model regressions, however, only the portfolios double sorted on lagged-assets-deflated cash-based operating profitability and the presented enterprise multiple maintain a statistically significant monthly alpha at a 5 % significance level.

Likewise, the self-financing portfolios double sorted on operating profitability and B/M generate an economically and at a 5 % significance level statistically significant monthly alpha relative to both factor models too. However, the main difference to the former considered two-dimensional portfolio strategies is that the strong performance of the double sorted profitability and B/M zero-cost portfolios is almost exclusively driven by the short side. Although the lowest quintile portfolios formed on profitability and B/M have strong negative exposures to the HML, RMW, and CMA factor, thus leading to lower estimates of their expected returns, these tilts are still insufficient to explain their low average monthly returns. In line with the findings of Fama and French (2016), it is seemingly small stocks whose returns behave like the ones of unprofitable firms that tend to invest aggressively which plague the Fama and French (2015) five-factor model. Meanwhile, the monthly returns of these low quintile portfolios can be well explained by factor exposures in a by BAB and QMJ extended Fama and French (1993) and Carhart (1997) four-factor regression. All of these low quintile portfolios have a highly negative loading on MOM and QMJ, while no longer generating monthly alpha relative to the extended multifactor model. This evidence inter alia suggests that the firms included in these portfolios share quality characteristics above and beyond the ones identified by the CMA and RMW factor that are relevant in asset pricing. As the monthly returns of the highest quintile portfolios formed on profitability and B/M similarly behave like the ones of unprofitable firms and junk stocks, it highlights once more that the positive RMW and QMJ factor loadings of the double sorted self-financing profitability and B/M portfolios are exclusively driven by the short-side of the trading strategy.

Hence, although a zero-cost portfolio double sorted on lagged-assets-deflated operating profitability and B/M generates the highest monthly excess returns and the highest monthly alpha relative to both factor models among the considered trading strategies, there are potentially issues in implementation for constrained and unconstrained investors. Consistent with prior findings that mispricing is likely to be more prevalent among low profitability stocks (Stambaugh et al. 2012), and that limits of arbitrage are associated with the returns of the gross- and cash-based operating profitability anomalies (DeLisle et al. 2020), investors may face challenges in actually implementing such an investment strategy due to arbitrage risk and short-sale constraints. While providing evidence thereon is beyond the scope of this thesis, the findings of this section also have important implications for contemporary value investors whose investment strategies are the primary focus of this thesis.

4.3 Portfolio optimization for constrained contemporary value investors

In fact, as most well-known contemporary value investors do not regularly engage in short selling, they face a fundamentally different investment optimization problem compared to unconstrained investors who control their risk through leverage, thus separating opportunity and exposure decisions. (Novy-Marx 2014) Hence, contemporary value investors have to evaluate risk and reward jointly. Correspondingly, the information content provided by the average long-only portfolio excess returns that are presented in Panel C of Table 7 is by itself insufficient to form a conclusion about the performance of an investment strategy. Moreover, constrained contemporary value investors are unlikely to rebalance their stock portfolio annually and usually rather stick to their investments for the long run. Consequently, as future profitability can be expected to be an important determinant of future stock prices and, thus, returns (e.g., Novy-Marx 2013), the overall profitability level of the firms included in the portfolio and the persistence therein increases in importance for contemporary value investors. Hence, apart from disparities among a portfolio's risk factor exposures and the abnormal returns the portfolio generates relative to the considered factor models, the overall profitability level of the firms included in the portfolio and the persistence therein influence the stock selection process of constrained contemporary value investors. Before providing evidence thereon, this section further reflects on differences in factor loadings among long-only double sorted portfolio strategies to deepen the discussion on potential risk-factor exposures.

For instance, all long-only portfolios double sorted on profitability and B/M have a pronounced value tilt by construction. While this observation does not lead to ground-breaking insights, this factor exposure is highly relevant as comprehensive evidence of prior research suggests that high B/M firms are riskier. Combined with the negative loading of these strategies on RMW and QMJ, which are presented in Panel C of Table 8, it points to concerns about the fundamental quality and the persistence of profitability of the firms included in these long-only portfolios.

While the long-only portfolios formed on the basis of profitability and B/M have yet to withstand the empirical tests concerning the level and persistence in profitability of the firms included in these portfolios, the evidence on hand strongly reminds of the finding of Kok et al. (2017) that quantitative investment strategies based on common fundamental metrics, such as book-to-market, systematically identify firms with temporarily inflated accounting numbers. In other words, when selecting firms with a high return on assets and a simultaneously high book-to-market ratio, the final portfolio will strongly tilt towards firms for which a particularly strong negative residual earnings growth is expected. This aligns with the findings of Penman et al. (2018) which suggest that for a given earnings yield, book-to-market indicates future earnings growth that is risky and that is associated with higher returns on average.

Similar concerns about the persistence of profitability among portfolio firms have been emphasized in the literature review about the Magic Formula and a portfolio double sorted on F-Score and B/M. Both investment strategies are suspected to proxy for a temporary underreaction to a firm's strength in fundamentals which is corrected as systematic errors in expectations unravel during subsequent earnings announcements. In fact, both long-only double sorted portfolios not only yield similar monthly excess returns, but they also have remarkably similar factor exposures in both multifactor regressions. Compared to all other considered long-only two-dimensional sorted portfolios, these two are the only ones that have a positive and statistically significant RMW factor loading. Overall, apart from the small cap tilt, the factor loadings of these portfolios rather exhibit a remarkable similarity with the ones of the 13-F stock portfolio of Berkshire Hathaway as shown by Frazzini et al. (2013). Hence, when it comes to publicly traded stocks, this study cannot reject the hypothesis of Greenblatt (2010) that the Magic Formula successfully proxies for Warren Buffett's investment principles. Still, both investment strategies fail to generate statistically significant abnormal returns relative to both factor models. Therefore, despite the remarkable similarities with Berkshire Hathaway's 13-F stock portfolio, double sorted profitability and enterprise multiple trading strategies are expected to better align the investment principles of contemporary value investors. The corresponding long-only portfolios might not only generate returns that remain unexplained by factor models, but also capture firms with a high level of profitability and a strong persistence therein.

Still, apart from a long-only portfolio formed on gross profitability and enterprise-value-deflated cash-based operating profitability, whose returns behave like the ones of unprofitable firms, all considered bivariate trading strategies that are sorted in combination with this enterprise multiple do not load statistically significantly on either the QMJ or RMW factor. However, if anything, these portfolios have a consistently positive loading on QMJ when considering the by BAB and QMJ extended Fama and French (1993) and Carhart (1997) four-factor regressions. Moreover, when using enterprise-value-deflated cash-based operating profitability instead of book-to-market to create bivariate portfolio strategies, all long-only portfolios, except for one formed on lagged-assets-deflated cash-based operating profitability and enterprise-value-deflated cash-based operating profitability, do not have a positive HML factor loading. In other words, the high average returns that these long-only two-dimensional sorted profitability and enterprise multiple portfolios generate have to be considered independent of the traditional value premium and the risk-based-explanations associated therewith.

Still, the regression results provide insufficient indications on whether using enterprise-value-deflated cash-based operating profitability instead of B/M as a value measure for bivariate portfolio sorts leads to a more successful selection of firms with persistent rather than temporarily inflated accounting numbers. While the portfolio companies of long-only double sorted profitability and enterprise multiple investment strategies may actually fail to exhibit strong profitability and profitability persistence characteristics, an alternative explanation is a failure of both multifactor asset pricing models to price these trading strategies. While the former explanation has yet to be tested empirically, the economically and at a 1 % significance level statistically significant monthly alpha that these long-only portfolios consistently generate relative to both factor models is strongly suggestive for the latter explanation.

5 Persistence of profitability

Hence, whether these double sorted portfolios fail to successfully proxy for the investment strategies of contemporary value investors due to deficient profitability characteristics among portfolio firms at the time of portfolio formation or over time will be investigated in detail in this section. As contemporary value investors invest for the long run and usually have a far below average portfolio turnover (e.g., Greenwald et al. 2004), future profitability as a determinant of future stock prices increases in importance for them. Before this analysis zeros in on a subsample of high B/M and low enterprise multiple firms, growth and value stocks are considered collectively to enhance the understanding of how the profitability among portfolio firms and the persistence therein changes when subsequently focusing exclusively on value firms.

Following Asness et al. (2019), z-scores for each indicator measure (gross-, operating-, and cash-based operating profitability) are constructed to analyse the persistence of profitability over time. All three profitability dimensions are simultaneously considered for each indicator measure. For example, when firms are sorted in ascending order based on the z-scores of gross profitability and are subsequently assigned to a quintile portfolio which is constructed using NYSE breakpoints, not only the persistence of these firms in gross profitability, but also in operating- and cash-based operating profitability is tested. Consistent with the prior section of this study, lagged assets are used as a deflator for the profitability measures. Table 9 correspondingly reports the time-series averages of the value-weighted cross-sectional z-score means for gross-, operating-, and cash-based-operating-profitability-sorted portfolios at the time of portfolio formation up to ten years after portfolio formation. The standard errors are adjusted according to Newey and West (1987) with a lag length of five years to account for potential autocorrelation and heteroskedasticity.

Although the profitability scores vary monotonically across portfolios at the time of portfolio formation by construction, this does not imply that each portfolio must have consistent rankings across all three considered profitability dimensions. However, in line with the strong positive Spearman rank correlations among the profitability measures, firms with high gross profitability tend to have a high operating- and cash-based operating profitability, while firms with low gross profitability tend to have a low operating- and cash-based operating profitability at the time of portfolio formation. In general, the highest profitability-sorted quintile portfolios are characterized by firms that have a high profitability across all profitability dimensions, while the lowest profitability-sorted quintile portfolios capture firms with an overall low level of profitability, irrespective of which profitability measure is used for portfolio sorts. The main question that remains, however, is whether this profitability is persistent over time across all three considered profitability dimensions.

Panel A of Table 9 presents the results for the sample which considers growth and value stocks collectively and shows that high profitability firms of today remain highly profitable in the future. The null hypothesis of no difference in each of the profitability characteristics can be rejected across all considered profitability dimensions up to ten years after portfolio formation. In other words, irrespective of which profitability metric is used for portfolio sorts, the corresponding portfolios exhibit strong persistence in gross-, operating-, and cash-based operating profitability over time. Still, using gross profitability as a sorting characteristic leads to a particularly desirable persistence in profitability across all three profitability dimensions. This is due to an on average lower mean-reversion in the value-weighted cross-sectional z-scores of both the highest and lowest quintile portfolio across all three profitability dimensions over time. In other words, the firms in the lowest gross-profitability-sorted quintile portfolio remain persistently unprofitable, while the highest gross-profitability-sorted quintile portfolio firms remain persistently profitable. As a result, the spread in the value-weighted cross-sectional z-scores of a high-minus-low portfolio is ten years after portfolio formation for all three considered profitability measures particularly pronounced when using gross profitability for portfolio sorts.

These findings are important to highlight as at the time of portfolio formation, the spread in the value-weighted cross-sectional z-scores of a high-minus-low profitability-sorted portfolio has by construction to be the highest for the profitability measure the portfolio sorting is based on. For example, although the spread in the cash-based operating profitability z-scores of a high-minus-low portfolio formed on cash-based operating profitability is the highest at the time of portfolio formation, this spread decreases considerably over time. The firms in the lowest quintile portfolio end up having above average cash-based operating profitability ten years after portfolio formation which points to a strong mean-reversion in cash-based operating profitability over time.

Hence, in order to get a better sense of these measures' power in predicting short-term and long-term growth in profitability, Fama and MacBeth (1973) regressions of profitability growth on current profitability are performed and presented in Panel A of Table 10. The dependent variables are defined as the change in profitability divided by the average lagged assets over the considered time horizon. The regressions include B/M, size, and the prior one-year returns as controls. In line with the observed mean-reversion in profitability for cash-based-operating profitability-sorted portfolios, current cash-based operating profitability has negative power in predicting short-term as well as long-term growth in cash-based operating profits, while having positive power in predicting the five- and ten-year growth in gross- and operating profits.

On the other hand, complementary to the findings of Novy-Marx (2013), current gross profitability is strongly positively predicting short-term as well as long-term growth in gross-, operating-, and cash-based operating profits, all measures which have been found to be important determinants of future stock prices in this study. Operating profitability has similar desirable characteristics when it comes to predicting short-term as well as long-term growth across all considered profitability dimensions. Still, two notable exceptions are an at a 5 % significance level statistically insignificant coefficient of gross profitability in predicting five-year operating profitability growth and an at a 5 % significance level statistically insignificant coefficient of operating profitability in predicting one- and five-year operating profitability growth. Collectively, these findings incrementally add to the evidence of Novy-Marx (2013) by showing that current operating- and gross profitability have power in predicting growth in profitability across all considered profitability dimensions. As both measures are strongly associated with contemporaneous valuation ratios, they can be expected to affect future valuations and, thus, returns.

Although the preceding analysis of the persistence in profitability did not focus on the value dimension explicitly, it serves as an important benchmark for the upcoming analysis on a subsample of value stocks. In order to provide evidence on the profitability persistence of the previously presented double sorted profitability and value investment portfolios, this study recycles the calculated z-scores and subsets the sample on the highest B/M and enterprise-value-deflated cash-based operating profitability quintile portfolio firms, respectively.

5.1 Persistence of profitability for high B/M firms

First, when considering the long-only portfolios formed on profitability and B/M, they are no longer expected to have consistent profitability rankings among all three profitability dimensions either at the time of portfolio formation or over time. This is due to prior observations which suggest that the monthly returns of long-only portfolios double sorted on profitability and book-to-market behave like the ones of firms with weak profitability and junk stock characteristics. Hence, there are not only concerns about the level of and consistency in profitability of the firms included in these portfolios at the time of portfolio formation, but also about their persistence in profitability over time. In fact, Panel B of Table 9 shows that in a subsample of low enterprise multiple firms the profitability-sorted portfolios no longer have consistent profitability rankings across all three profitability dimensions either at the time of portfolio formation or over time. For instance, the highest cash-based-operating-profitability-sorted quintile portfolio is composed of firms that tend to have below average gross profitability at the time of portfolio formation. In fact, both the lowest and the highest cash-based-operating-profitability-sorted quintile portfolio is consistently associated with below average gross profitability up to ten years after portfolio formation. Correspondingly, the gross profitability z-score spread between the highest and lowest cash-based-operating profitability-sorted portfolio is ten years after portfolio formation no longer statistically significant and, thus, points to a lack of persistence in gross profitability.

While the highest gross- and operating-profitability-sorted quintile portfolios are still associated with above average profitability across all three profitability dimensions at the time of portfolio formation, these associations change one year after portfolio formation. Apparently, the mean-reversion in profitability among portfolio firms is so strong in the first year after portfolio formation as to simultaneously lead to below average gross profitability for all operating-profitability-sorted portfolios and to below average operating- and cash-based operating profitability for all gross-profitability-sorted portfolios. The spreads in z-scores between the highest and lowest profitability-sorted quintile portfolios remain statistically significant over time, irrespective of which portfolio sorting characteristic is used. This consistency, however, largely reflects the tendency of a portfolio of unprofitable value firms to maintain below average profitability across all three considered profitability dimensions over time.

The Fama and MacBeth (1973) regressions presented in Panel B of Table 10 complement the findings concerning a weak persistence in profitability for traditional value firms. When focusing on a subsample of high B/M firms, cash-based operating profitability is a negative predictor of the one-year ahead growth in gross-, operating-, and cash-based operating profits. Holding all else equal, an increase in current cash-based operating profits by one dollar is associated with a 43 cent average one year decrease in cash-based operating profits, being more than twice as large as the 19 cent average one year decrease in cash-based operating profits in a sample which considers value and growth firms collectively. This finding is no longer specific to cash-based operating profitability as operating profitability is an economically and at a 5 % significance level statistically significant negative predictor of the future one-year growth across all three profitability dimensions as well. Meanwhile, current gross profitability has lost its predictive power for long-term growth in gross profits and negatively predicts growth in operating profits across all considered time horizons.

Collectively these findings suggest that irrespective of which profitability measure is used for portfolio sorts, the mean-reversion in profitability in the first year after portfolio formation is for firms of long-only portfolios formed on the basis of profitability and book-to-market particularly pronounced across all profitability dimensions. This evidence aligns with the findings of Kok et al. (2017) and Penman et al. (2018). In other words, the portfolio firms of these two-dimensional trading strategies appear to have on average profitability characteristics that point to a temporary inflation of accounting numbers at the time of portfolio formation. In contrast to the conclusion of prior research that a double sorted profitability and B/M portfolio strategy helps in separating winners from losers (e.g., Piotroski 2000) and in identifying an underreaction of market participants to a strength in fundamentals, the evidence of this study strongly suggests that the initial level of profitability of the firms included in these portfolios cannot be sustained over time. Hence, combined with the factor regression results, the findings of this study align with risk-based explanations of prior research (e.g., Penman et al. 2018).

However, the presented evidence does not rule out that errors-in-expectations among investors might play a role in explaining the return performance of zero-cost portfolios formed on profitability and B/M in general. According to the findings of a prior section of this study, the strong abnormal monthly return performance of the self-financing portfolios double sorted on profitability and B/M relative to factor models is almost exclusively driven by the short side. Long-only portfolios formed on profitability and B/M overwhelmingly fail to generate abnormal returns relative to the considered factor models. On the other hand, the strong negative exposures to the HML, RMW, and CMA factor are insufficient to explain the low average returns of short-only portfolios double sorted on profitability and B/M. Hence, consistent with prior findings that mispricing is likely to be more prevalent among low profitability stocks (Stambaugh et al. 2012), and that limits of arbitrage are associated with the returns of the gross-and cash-based operating profitability anomalies (DeLisle et al. 2020), errors-in-expectations of investors might play a role among these short-only portfolios. However, providing evidence thereon is beyond the scope of this thesis and this study rather encourages future research to investigate the matter. Meanwhile, for contemporary value investors who invest long-only with a long-term investment horizon, this evidence is sobering and a long-only two-dimensional sorted profitability and B/M portfolio strategy is in conflict with the investment principles of contemporary value investors when it comes to the persistence in profitability among portfolio firms.

5.2 Persistence of profitability for high CBOP/EV firms

Not the least because the considered long-only portfolios formed on the basis of profitability and B/M are subject to risk-based explanations might a two-dimensional sorted profitability and enterprise multiple investment strategy better align with the investment principles of contemporary investors. Except for when using lagged-assets-deflated cash-based operating profitability for bivariate portfolio sorts, the monthly returns of all double sorted profitability and enterprise-multiple portfolio strategies have been shown to behave like the ones of growth stocks in a prior section of this study. Still, the statistically insignificant loadings on RMW and QMJ have casted doubt on whether these investment strategies withstand the tests concerning the level and persistence of profitability among portfolio firms.

Correspondingly, Panel C of Table 9 presents the value-weighted average of profitability z-scores across profitability-sorted portfolios for a subsample of high enterprise-value-deflated cash-based operating profitability quintile portfolio firms. Irrespective of which profitability measure is used for portfolio sorts, the highest profitability-sorted quintile portfolio is comprised of firms that have an on average high profitability across all three profitability dimensions at the time of portfolio formation. Meanwhile, the lowest profitability-sorted quintile portfolio captures firms with an on average low level of profitability across all profitability dimensions at the time the portfolio is formed. The average z-scores of the highest profitability-sorted quintile portfolios are lower across all three profitability dimensions at the time of portfolio formation compared to the ones observed in a sample in which growth and value stocks are considered collectively. Still, the high profitability-sorted quintile portfolios have in a subsample of high enterprise-value-deflated cash-based operating profitability firms consistently higher levels of profitability compared to the ones observed in a subsample of high book-to-market firms, which is presented in Panel B of Table 9.

In fact, the fundamental difference among the two-dimensional portfolios formed on the basis of profitability and value becomes even more prevalent when comparing their portfolio firms' persistence in profitability. When focusing on a subsample of low enterprise multiple firms, highly profitable firms of today remain highly profitable in the future, irrespective of which profitability metric is used for portfolio sorts. The mean-reversion in profitability that has been documented among high B/M firms one year after portfolio formation is weak to non-existent among the highest profitability-sorted quintile portfolios, whereas the mean-reversion in profitability is particularly pronounced among the lowest profitability-sorted quintile portfolios. Hence, while the spread in profitability z-scores of all high-minus-low profitability-sorted portfolios is shrinking over time, this effect is overwhelmingly attributable to the lowest quintile portfolios that, irrespective of which profitability sorting characteristic is used, end up having above average cash-based operating profitability ten years after portfolio formation. In other words, the evidence collectively suggests that a high enterprise-value-deflated cash-based-operating-profitability-sorted quintile portfolio is on average not only associated with highly profitable firms, but also with ones for which future profitability consistently improves on average.

Although the null hypothesis of no difference in each of the profitability characteristics can be rejected for all specifications up to ten years after portfolio formation, using gross profitability as a sorting variable leads again to particularly desirable persistence characteristics across all three profitability dimensions. In a subsample of low enterprise multiple firms, the value-weighted cross-sectional z-scores of a high gross-profitability-sorted portfolio are ten years after portfolio formation for all three considered profitability dimensions the highest. Moreover, in the first year after portfolio formation, the value-weighted cross-sectional operating- and cash-based operating profitability z-scores even increase for the highest gross-profitability-sorted quintile portfolio. This finding is suggestive for a strong profitability growth across both profitability dimensions in the first year after portfolio formation when focusing on a subsample of high enterprise-value-deflated cash-based operating profitability quintile portfolio firms.

Accordingly, this evidence on the desirable profitability characteristics among portfolio firms of long-only portfolios double sorted on profitability and enterprise-value-deflated cash-based operating profitability is complemented by the Fama and MacBeth (1973) regression results which are presented in Panel C of Table 10. When interpreting the corresponding results, however, it is crucial to account for the strong mean-reversion in profitability among the lowest profitability-sorted quintile portfolios in a sample of low enterprise multiple firms, before drawing inferences on the persistence of profitability based on the regression results. For instance, when considering the lowest profitability-sorted quintile portfolios of a subsample of high book-to-market stocks in comparison, the mean-reversion in profitability among their lowest profitability-sorted quintile portfolios is far less pronounced and unprofitable firms overwhelmingly remain unprofitable in the future. Hence, this tendency is affecting the corresponding coefficient of the independent profitability variable in the regression. Correspondingly, despite the observed weak mean reversion in z-scores among the highest operating- and cash-based-operating-profitability-sorted quintile portfolios in a subsample of low enterprise multiple firms, current operating- and cash-based operating profitability negatively predict the one-year growth in operating profits. However, despite the strong mean-reversion in profitability z-scores among the lowest gross-profitability-sorted quintile portfolio in a subsample of low enterprise multiple firms over time, gross profitability has power predicting short-term as well as long-term growth in gross-, operating-, and cash-based operating profits. All these measures have been found to be important determinants of future stock prices in this study.

Most remarkably, and in line with the value-weighted cross-sectional z-scores of a high gross-profitability-sorted quintile portfolio, the predictive power of current gross profitability on the five- and ten-year growth in operating- and cash-based operating profits is in a subsample of low enterprise multiple firms even stronger compared to the one observed in a sample which considers growth and value firms collectively. For instance, an increase in current gross profits by one dollar is ceteris paribus associated with a 12-cent average ten-year increase in cash-based operating profits when focusing on low enterprise multiple firms. This compares with a 7-cent average ten-year increase in cash-based operating profits when considering growth and value firms collectively and a 5-cent average ten-year decrease in cash-based operating profits when focusing exclusively on high book-to-market firms. Likewise, the predictive power of gross profitability for the growth in gross profits is in a subsample of high enterprise-value-deflated cash-based operating profitability firms comparable to the one when considering growth and value firms collectively. For instance, an increase in current gross profits by one dollar is ceteris paribus associated with a 46-cent average ten-year increase in gross-profits in both regression specifications.

Therefore, the firms included in a long-only portfolio formed on the basis of gross profitability and enterprise-value-deflated cash-based operating profitability not only resemble growth stocks in terms of both characteristics and covariances, but they also exhibit a high level of profitability and a strong persistence therein over time. Collectively, these findings make it difficult to reconcile the strong return performance of these two-dimensional sorted portfolios with the mentioned risk-based explanations of the value premium. This evidence compares with the findings on long-only portfolios double sorted on profitability and B/M which suggest that these portfolios fail to have consistent profitability rankings among all three profitability dimensions either at the time of portfolio formation or over time. Hence, these two-dimensional portfolio strategies fail to align with the investment principles of contemporary value investors when it comes to the persistence in profitability among portfolio firms over time.

6 Conclusion

This study has introduced portfolios doubled sorted on profitability and value that aim to proxy for the investment principles of contemporary value investors. Enterprise-value-deflated operating income and enterprise-value-deflated cash-based operating profitability are used as alternative value measures to move beyond the narrow definition of value investing as book-to-market investing. Thereby, this study shows that these valuation ratios capture a highly dissimilar information content. While B/M is negatively correlated with all considered profitability measures, both enterprise-value-deflated accounting measures show a moderate positive correlation with all considered profitability variables. If anything, a high enterprise-value-deflated cash-based-operating-profitability-sorted quintile portfolio captures on average highly profitable firms and ones for which future profitability consistently improves on average. Compared to a self-financing portfolio formed on B/M, it not only generates economically and statistically significant abnormal returns relative to a Fama and French (2015) five-factor and a by BAB and QMJ extended Fama and French (1993) and Carhart (1997) four-factor model, but its monthly returns also behave like the ones of firms with robust profitability and high quality. Collectively, these findings imply that even without accounting for the profitability dimension explicitly, the right valuation ratio choice can prevent the investor from a portfolio tilt towards unprofitable firms and junk stocks.

When it comes to profitability measure choice, this study complements and incrementally adds to the findings of Ball et al. (2016) by documenting a strong predictive power of cash-based operating profitability for expected returns, irrespective of deflator choice. For instance, lagged-assets-deflated cash-based operating profitability subsumes accruals as well as operating- and gross profitability in predicting the cross-section of average returns. This observation challenges the conclusion of Sloan (1996) that investors behave as if accruals and cash flows are equally persistent. Instead, the evidence points to a predictive power of accruals that largely results from the tendency of high-accrual firms to have an on average lower cash-based operating profitability. In line with the conclusion of Ball et al. (2016), this evidence is collectively indicating that accruals allow the regression to extract the cash-based component from the accruals-based profitability variable. This effect appears to be so strong as to reflect itself even when using conceptually and fundamentally different deflators, as enterprise-value-deflated cash-based operating profitability is subsuming accruals in predicting the cross-section of average returns as well.

These findings serve as the basis for the construction of two-dimensional sorted portfolio strategies and help in understanding the conceptual and fundamental differences among them. For instance, self-financing portfolios formed on operating profitability and B/M generate economically and statistically significant abnormal returns relative to a Fama and French (2015) five-factor as well as a by BAB and QMJ extended Fama and French (1993) and Carhart (1997) four-factor model. However, the main difference to zero-cost portfolios double sorted on profitability and enterprise-value-deflated cash-based operating profitability is that the strong performance of the former is almost exclusively driven by the lowest quintile portfolios. Although the lowest quintile portfolios formed on profitability and B/M have strong negative exposures to the HML, RMW, and CMA factor, thus leading to lower estimates of their expected returns, these tilts are still insufficient to explain their low average returns.

As the portfolio returns of the highest double sorted profitability and B/M quintile portfolios simultaneously behave like the ones of unprofitable firms and junk stocks, it highlights that the positive RMW and QMJ factor loadings of the self-financing portfolios sorted on profitability and B/M are strongly driven by the short-side of the trading strategy. Particularly from the viewpoint of constrained long-only contemporary value investors, this evidence is leading to concerns about the level and persistence of fundamental quality among portfolio firms. In fact, the long-only portfolios double sorted on profitability and B/M not only fail to have consistent profitability rankings among all considered profitability dimensions either at the time of portfolio formation or over time, but their portfolio firms also exhibit a strong mean reversion in profitability one year after portfolio formation. For example, in a subsample of high B/M firms, operating and cash-based operating profitability are an economically and at a 5 % significance level statistically significant negative predictor of the future one-year growth across all three considered profitability dimensions.

While the monthly returns of long-only portfolios double sorted on profitability and B/M are correspondingly subject to risk-based explanations, the monthly returns of long-only bivariate sorted profitability and enterprise multiple investment strategies are difficult to reconcile with explanations based on the traditional value premium. In fact, except for when using lagged-assets-deflated cash-based operating profitability for bivariate sorts, the returns of all two-dimensional long-only investment strategies behave like the ones of growth stocks. Still, the statistically insignificant loadings on RMW and QMJ have casted doubt on whether these portfolio strategies withstand the tests concerning the level and persistence of profitability among portfolio firms. However, when focusing on a subsample of low enterprise multiple stocks, highly profitable firms of today remain highly profitable in the future, irrespective of which profitability measure is used for portfolio sorts. The highest profitability-sorted quintile portfolios are characterized by firms that have a high profitability across all profitability dimensions over time, while the lowest profitability-sorted quintile portfolios consistently capture firms with a low level of profitability across all profitability dimensions. Hence, instead of revealing temporary inflated accounting numbers among portfolio firms, the evidence points to a failure of both multifactor asset pricing models to price the two-dimensional long-only profitability and enterprise multiple investment strategies. These portfolios consistently generate an economically and at a 1 % significance level statistically significant alpha relative to both considered factor models.

Finally, in line with the evidence of Novy-Marx (2013), gross profitability has a particularly strong power in predicting profitability growth among all three considered profitability measures. In this study, gross profitability has power predicting short-term as well as long-term growth in gross-, operating-, and cash-based operating profits, all measures which have been found to be important determinants of future stock prices in this study. Most remarkably, the power of current gross profitability in predicting the five- and ten-year growth in operating- and cash-based operating profits is in a subsample of low enterprise multiple firms even stronger than in a sample in which growth and value stocks are considered collectively. Hence, firms that are included in a double sorted high gross-profitability and enterprise-value-deflated cash-based operating profitability portfolio not only resemble growth stocks in terms of both characteristics and covariances, but they also exhibit a high level of profitability and a strong persistence therein over time.

However, this evidence is by itself insufficient to establish a direct link between the strong persistence in profitability among portfolio firms and the strong return performance that two-dimensional sorted profitability and enterprise multiple investment strategies exhibit. First, further research that complements current literature on the potential sources of the profitability and value premium is necessary to enhance our understanding of the underlying factor drivers. Second, as this study considers the profitability and value dimension jointly, future research has yet to provide evidence on whether enterprise-value-deflated cash-based operating profitability resembles lagged-asset-deflated cash-based operating profitability in predicting returns up to ten years into the future as observed by Ball et al. (2016). Instead, in line with an errors-in-expectations hypothesis, the abnormal return performance of an investment portfolio formed on enterprise-value-deflated cash-based operating profitability might, complementary to other value strategies, be concentrated around subsequent quarterly earnings announcements and might not persist into the second year of the investment strategy.

Still, this study recurrently provides evidence for pronounced differences in information content among the considered value measures which rather suggest that there is a substantial common component among enterprise-value-deflated cash-based operating profitability and the considered profitability variables. Correspondingly, if cash-based operating profitability scaled by enterprise value predicts returns over longer time horizons, it would lead the way for two streams of research. First, in line with the findings of Ball et al. (2016), the strong return performance could be related to behavioural explanations. For instance, it could be related to an initial underreaction of investors to cash flow information that is gradually corrected over time. Second, a persistent predictability of returns might together with the considered profitability measures point to common risk factor exposures that are rather stationary over time.

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Table 1: Descriptive statistics

This table presents the distributions of the variables used in subsequent analysis, or the time-series average of the cross-sectional means and cross-sectional standard deviations as well as the time series averages of the percentiles, more specifically. The profitability measures gross profitability (GP), operating profitability (OP), and cash-based operating profitability (CBOP) are scaled by lagged assets. Piotroski's (2000) F-Score and return on capital employed (ROCE) are used as alternative profitability variables, while log (B/M) as the natural logarithm of the book-to-market ratio, EBIT/EV as earnings before interest and taxes scaled by enterprise value, and CBOP/EV as cash-based operating profitability scaled by enterprise value are used as valuation measures. The construction of the accounting variables is in detail explained in the Appendix. The other variables used in the analysis are defined as follows: ACC as accruals deflated by the average of contemporaneous and lagged assets; log (ME) as the natural logarithm of the market value of equity; $r_{1,1}$ as the prior one-month return; $r_{12,2}$ as the prior year's return skipping the last month; and r_{1f} as the one-month ahead return. The sample period starts in July 1963 and ends in November 2019. This study includes all firms traded on NYSE, AMEX, and NASDAQ, and excludes securities other than ordinary common shares. Firms are required to have non-missing values for the following items: market value of equity, book-to-market, gross profit, and book value of total assets. Financial firms, defined as firms with one-digit SIC codes of six, are excluded from this analysis. The time-series averages of the cross-sectional means and standard deviations of the accounting variables are reported after the according profitability measures have been winsorized at the 1st and 99th percentile.

	Distributions						
			Percentiles				
Variable	Mean	SD	1st	25th	50th	75th	99th
Profitability measures deflated by lagged assets							
Gross profitability (GP)	0.416	0.339	-0.522	0.195	0.369	0.584	1.566
Operating profitability (OP)	0.146	0.178	-0.550	0.076	0.148	0.232	0.675
Cash-based operating profitability (CBOP)	0.121	0.186	-0.657	0.054	0.133	0.213	0.625
Valuation measures							
Log (B/M)	-0.582	0.902	-3.311	-1.121	-0.508	0.037	1.356
EBIT/EV	0.043	0.204	-1.078	0.008	0.073	0.121	0.629
CBOP/EV	0.123	0.213	-0.728	0.040	0.111	0.191	1.178
Other variables used in regressions or portfolio sorts							
Accruals (ACC)	-0.030	0.134	-0.498	-0.083	-0.032	0.021	0.461
F-Score	5.290	1.648	1.000	4.000	5.000	6.000	9.000
ROCE	0.044	1.628	-8.809	0.019	0.101	0.206	9.137
Log(ME)	4.742	2.222	0.266	3.074	4.591	6.291	10.342
$r_{1,1}$	0.012	0.191	-0.404	-0.071	0.000	0.075	0.596
$r_{12,2}$	0.144	0.750	-0.821	-0.217	0.047	0.334	2.641
r_{1f}	0.012	0.191	-0.402	-0.071	0.000	0.075	0.593

Table 2: Spearman-rank correlations

This table presents the Spearman rank correlations of the variables of interest in this study. Consistent with the deflated profitability variables shown in Table 1, profitability measures are scaled by lagged assets (LA), or in the case of ROCE, by capital employed.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) r_{1f}	-											
(2) Gross profitability (GP)	0.017	-										
(3) Operating profitability (OP)	0.043	0.593	-									
(4) Cash-based operating profitability (CBOP)	0.047	0.409	0.763	-								
(5) ROCE	0.043	0.441	0.683	0.534	-							
(6) F-Score	0.038	0.123	0.283	0.320	0.294	-						
(7) Accruals	0.002	0.223	0.240	-0.146	0.296	-0.004	-					
(8) Log(B/M)	0.031	-0.209	-0.300	-0.233	-0.255	0.055	-0.077	-				
(9) EBIT/EV	0.063	0.308	0.521	0.398	0.573	0.375	0.218	0.296	-			
(10) CBOP/EV	0.057	0.135	0.305	0.609	0.206	0.315	-0.286	0.375	0.557	-		
(11) $r_{12,2}$	0.039	0.054	0.113	0.130	0.112	0.136	-0.006	0.072	0.174	0.158	-	
(12) Log(ME)	0.034	-0.053	0.271	0.282	0.299	0.082	0.020	-0.401	0.007	-0.041	0.034	-

Table 3: Profitability in Fama and MacBeth (1973) regressions:

This table reports average Fama and MacBeth (1973) regression slopes (multiplied by 100) from cross-sectional regressions that predict monthly returns. Their corresponding t-values are presented in parenthesis. The regressions are estimated using monthly data based on the sample described in Table 1. For the profitability measures in regressions (1)-(3), lagged book value of assets is used as a deflator. The natural logarithm of B/M, the natural logarithm of market capitalization, and the prior month as well as prior 12-month period excluding month t-1 returns are used as control variables. All independent variables are winsorized at the 1st and 99th percentiles and microcaps, which are defined as stocks with market values of equity below the 20th percentile of the NYSE market cap distribution, are excluded from this analysis.

	Accounting variables deflated by		
	Lagged total assets		
Regressor	(1)	(2)	(3)
Gross profitability (GP)	0.3633 (3.32)		
Operating profitability (OP)		1.3803 (5.84)	
Cash-based operating profitability (CBOP)			1.8253 (9.57)
Log(B/M)	0.2564 (3.81)	0.3046 (4.55)	0.2974 (4.36)
Log(ME)	-0.0304 (-0.84)	-0.0425 (-1.18)	-0.0582 (-1.63)
$r_{1,1}$	-3.6891 (-8.73)	-3.6369 (-8.59)	-3.6836 (-8.70)
$r_{12,2}$	0.6585 (3.29)	0.6484 (3.24)	0.6045 (3.02)
Observations		854,118	
R-Squared	0.2655	0.2651	0.2646

Table 4: Profitability and accruals in Fama and MacBeth (1973) regressions:

This table reports average Fama and MacBeth (1973) regression slopes (multiplied by 100) from cross-sectional regressions that predict monthly returns. Their corresponding t-values are presented in parenthesis. The regressions are estimated using monthly data based on the sample described in Table 1. Regressions (1)-(4) test whether the considered profitability variables maintain their predictive power for the cross-section of returns when controlling for accruals, while regressions (5)-(7) test whether there is a profitability measure that subsumes the predictive power of the others for the cross-section of returns. The natural logarithm of B/M, the natural logarithm of market capitalization, and the prior month as well as prior 12-month period excluding month t-1 returns are used in addition to accruals as control variables. All independent variables are winsorized at the 1st and 99th percentiles and microcaps, which are defined as stocks with market values of equity below the 20th percentile of the NYSE market cap distribution, are excluded from this analysis.

	Accounting variables deflated by						
	Lagged total assets						
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GP		0.4321 (3.95)			0.0924 (0.77)		0.1294 (0.98)
OP			1.5760 (6.70)			-0.0308 (-0.09)	-0.2708 (-0.75)
CBOP				1.7891 (8.83)	1.7609 (8.23)	1.8532 (6.62)	1.9072 (6.91)
Accruals	-0.8224 (-3.37)	-1.0123 (-4.32)	-1.1071 (-4.70)	-0.1888 (-0.74)	-0.2883 (-1.17)	-0.2340 (-0.90)	-0.2286 (-0.89)
Log(B/M)	0.1584 (2.50)	0.2348 (3.58)	0.2852 (4.34)	0.2887 (4.38)	0.3046 (4.56)	0.2923 (4.44)	0.2958 (4.46)
Log(ME)	-0.0428 (-1.19)	-0.0385 (-1.07)	-0.0531 (-1.49)	-0.0588 (-1.66)	-0.0589 (-1.67)	-0.0595 (-1.68)	-0.0578 (-1.64)
$r_{1,1}$	-3.5879 (-8.47)	-3.7250 (-8.86)	-3.6747 (-8.72)	-3.6942 (-8.77)	-3.8278 (-9.18)	-3.7303 (-8.89)	-3.8717 (-9.32)
$r_{12,2}$	0.6665 (3.31)	0.6448 (3.22)	0.6317 (3.16)	0.6046 (3.03)	0.5976 (3.01)	0.6108 (3.07)	0.5958 (3.01)
Observations		849,537				849,537	
R-Squared	0.2638	0.2678	0.2674	0.2671	0.2689	0.2710	0.2728

Table 5: Value, profitability, and accruals in Fama and MacBeth (1973) regressions:

This table reports average Fama and MacBeth (1973) regression slopes (multiplied by 100) from cross-sectional regressions that predict monthly returns. Their corresponding t-values are presented in parenthesis. The regressions are estimated using monthly data based on the sample described in Table 1. Regressions (1)-(3) test the predictive power of valuation measures for the cross-section of returns and regression (4) provides evidence on whether there is a valuation measure that subsumes the predictive power of the other value measures for the cross-section of returns. Regression (5)-(6) further highlight differences in information content among the considered valuation metrics when controlling for accruals, while in regression (7) profitability and value measures are used as independent variables. The natural logarithm of B/M, the natural logarithm of market capitalization, and the prior month as well as prior 12-month period excluding month t-1 returns are used in addition to accruals as control variables. All independent variables are winsorized at the 1st and 99th percentiles and microcaps, which are defined as stocks with market values of equity below the 20th percentile of the NYSE market cap distribution, are excluded from this analysis.

	Accounting variables deflated by						
	Lagged total assets						
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GP							0.0984 (0.75)
OP							-0.2439 (-0.54)
CBOP							1.5707 (4.17)
Accruals					-1.2002 (-4.19)	-0.4332 (-1.54)	-0.1323 (-0.51)
EBIT/EV	2.1567 (3.80)			0.9576 (1.75)	2.3067 (4.03)		0.6051 (0.88)
CBOP/EV		1.8903 (6.35)		1.5117 (6.05)		1.9513 (6.77)	0.4733 (1.25)
Log(B/M)			0.1864 (2.83)	0.0942 (1.52)			0.2293 (3.72)
Log(ME)	-0.0545 (-1.57)	-0.0572 (-1.62)	-0.0353 (-0.97)	-0.0462 (-1.30)	-0.0612 (-1.78)	-0.0579 (-1.66)	-0.0578 (-1.68)
$r_{1,1}$	-3.3513 (-7.83)	-3.3543 (-7.73)	-3.5705 (-8.37)	-3.7470 (-8.99)	-3.4390 (-8.12)	-3.3892 (-7.86)	-3.9989 (-9.86)
$r_{12,2}$	0.6731 (3.40)	0.6532 (3.23)	0.6773 (3.36)	0.6226 (3.18)	0.6478 (3.28)	0.6388 (3.17)	0.5737 (2.97)
Observations	874,363	874,367	858,427		865,371		849,537
R-Squared	0.2556	0.2513	0.2606	0.2685	0.2604	0.2555	0.2814

Table 6: Univariate sorted portfolio strategies – return characteristics:

This table reports the monthly excess returns of univariate sorted zero-cost profitability and value investment portfolios together with corresponding return correlations. In each year at the end of June, firms are sorted in ascending order based on a profitability or value measure and are subsequently assigned to a quintile portfolio which is constructed using NYSE breakpoints. The accounting variables are deflated by the book value of lagged assets. In Panel A, the time series average of the monthly excess returns is reported for each indicator measure, whereby zero-cost refers to the time series average of the monthly excess returns of a long-short extreme quintile portfolio. Panel B presents the Pearson return correlations for the corresponding portfolios.

Panel A: Zero-cost portfolio returns

Variable	GP	OP	CBOP	F-Score	B/M	EBIT/EV	CBOP/EV
Monthly average excess returns	0.2345	0.2055	0.3511	0.4483	0.3308	0.5348	0.6310
t-statistic	2.0233	1.8501	3.2478	4.1427	2.3753	3.7988	5.2544

Panel B: Pearson return correlations

Variable	GP	OP	CBOP	F-Score	B/M	EBIT/EV	CBOP/EV
GP	-						
OP	0.6793	-					
CBOP	0.4179	0.8248	-				
F-SCORE	-0.0264	0.3811	0.4385	-			
B/M	-0.6575	-0.5011	-0.3727	0.0584	-		
EBIT/EV	-0.3137	0.0943	0.1618	0.4602	0.5757	-	
CBOP/EV	-0.4042	-0.0578	0.1332	0.2787	0.6507	0.7988	-

Table 7: Double sorted portfolio strategies – return characteristics:

This table reports the monthly excess returns of double sorted zero-cost profitability and value investment portfolios together with corresponding return correlations as well as with the monthly excess returns of long-only two-dimensional investment strategies. In each year at the end of June, firms are sorted in ascending order based a profitability or value measure and are subsequently assigned to a quintile portfolio which is constructed using NYSE breakpoints. The double sorting procedure is unconditional and correspondingly based on the intersection between the univariate sorted quintile portfolios. The accounting variables are deflated by the book value of lagged assets, except for CBOP_LCE which refers to cash-based operating profitability scaled by lagged capital employed. In Panel A, the time series average of the monthly excess returns is reported for each double sorted investment portfolio, whereby zero-cost refers to the time series average of the monthly excess returns of a long-short extreme quintile portfolio. Panel B presents the Pearson return correlations of the corresponding portfolios. In Panel C, the time series average of the monthly excess returns of the highest quintile portfolios are presented.

Panel A: Zero-cost portfolio returns of double sorted profitability- and value investment strategies

Profitability measure	F-Score	GP	OP	CBOP	ROCE	GP	OP	CBOP	CBOP_LCE
Value measure	B/M	B/M	B/M	B/M	EBIT/EV	CBOP/EV	CBOP/EV	CBOP/EV	CBOP/EV
Monthly average excess returns	0.7758	0.8329	1.3274	1.1505	0.6346	0.6879	0.7868	0.7777	0.7005
t-statistic	3.8630	3.5404	4.1085	4.1402	3.7617	3.9512	4.5805	5.5658	5.3331

Panel B: Pearson return correlations of double sorted profitability- and value investment strategies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) F-Score and B/M	-								
(2) GP and B/M	0.2901	-							
(3) OP and B/M	0.3145	0.4037	-						
(4) CBOP and B/M	0.3885	0.3992	0.7133	-					
(5) ROCE and EBIT/EV	0.3367	0.2193	0.2275	0.2512	-				
(6) GP and CBOP/EV	0.1121	0.2529	0.1310	0.0801	0.3459	-			
(7) OP and CBOP/EV	0.2600	0.0775	0.3038	0.2799	0.5558	0.5818	-		
(8) CBOP and CBOP/EV	0.3107	0.0618	0.2482	0.3572	0.5365	0.4775	0.8735	-	
(9) CBOP_LCE CBOP/EV	0.2150	0.1050	0.1673	0.2532	0.5798	0.5492	0.7920	0.8435	-

Panel C: Long-only portfolio returns of double sorted profitability- and value strategies

Profitability measure	F-Score	GP	OP	CBOP	ROCE	GP	OP	CBOP	CBOP_LCE
Value measure	B/M	B/M	B/M	B/M	EBIT/EV	CBOP/EV	CBOP/EV	CBOP/EV	CBOP/EV
Monthly average excess return	0.8781	0.8147	1.1977	0.9529	0.8870	0.9248	0.9514	0.9637	0.9058
t-statistic	4.6131	2.8051	3.2989	2.9965	4.3438	4.0213	4.5394	4.8794	4.2842

Table 8: Factor loadings of univariate and double sorted profitability- and value portfolios:

This table presents the regressions of the monthly value-weighted average excess returns of the considered portfolio strategies on factor-mimicking portfolio returns. This study applies the Fama and French (2015) five-factor model and a by BAB (betting-against-beta) and QMJ (quality-minus-junk) extended Fama and French (1993) and Carhart (1997) four-factor model. Alpha is referring to the monthly value-weighted average excess returns to univariate portfolios formed on profitability and value measures after controlling for factor exposures. The explanatory variables in the five-factor model specification are the monthly returns from the market portfolio (MKT), size (SMB), book-to-market (HML), profitability (RMW), and investment (CMA) factor-mimicking portfolios, while in the extended four-factor model they are the monthly returns from the market portfolio (MKT), size (SMB), book-to-market (HML), momentum (UMD), betting against beta (BAB), and quality (QMJ) factor-mimicking portfolios. In Panel A, the monthly value-weighted excess returns of the univariate sorted zero-cost profitability and value portfolios are used as dependent variables in the regressions, while Panel B-D consider the returns of double sorted portfolio strategies. Panel B presents the regression results for self-financing portfolios, while Panel C and D are focused on long-only and short-only double sorted profitability and value portfolios.

Panel A: Factor loadings of univariate sorted self-financing profitability and value portfolios

	Alpha	MKT	SMB	HML	UMD	RMW	CMA	BAB	QMJ	Adj R^2
GP	0.307	0.043	0.083	-0.405		0.399	-0.348			40.3 %
	(3.27)	(1.85)	(2.55)	(-9.03)		(8.74)	(-5.19)			
	0.001	0.250	0.223	-0.351	0.011			-0.214	0.842	50.0 %
	(0.01)	(10.66)	(7.05)	(-10.06)	(0.53)			(-7.40)	(16.35)	
OP	0.299	-0.072	-0.155	-0.374		0.585	-0.209			46.9 %
	(3.53)	(-3.42)	(-5.25)	(-9.22)		(14.16)	(-3.44)			
	-0.117	0.141	-0.050	-0.239	0.145			-0.116	0.869	58.8 %
	(-1.50)	(6.93)	(-1.83)	(-7.88)	(7.76)			(-4.64)	(19.40)	
CBOP	0.480	-0.124	-0.339	-0.380		0.388	0.110			44.9 %
	(3.53)	(-5.91)	(-11.61)	(-9.47)		(9.48)	(1.83)			
	0.128	0.030	-0.244	-0.138	0.168			-0.075	0.674	61.8 %
	(1.75)	(1.57)	(-9.47)	(-4.87)	(9.62)			(-3.21)	(16.05)	
B/M	-0.082	-0.020	0.255	0.872		0.029	0.339			69.1 %
	(-1.01)	(-1.01)	(9.05)	(22.47)		(0.74)	(5.86)			
	0.020	-0.102	0.188	0.961	0.032			0.116	-0.222	69.0 %
	(0.24)	(-4.59)	(6.29)	(29.13)	(1.58)			(4.23)	(-4.55)	
CBOP/EV	0.298	-0.039	0.059	0.465		0.293	0.450			48.5 %
	(3.30)	(-1.72)	(1.88)	(10.76)		(6.66)	(6.97)			
	0.250	-0.026	0.055	0.763	0.133			-0.027	0.227	47.5 %
	(2.62)	(-1.03)	(1.63)	(20.61)	(5.83)			(-0.88)	(4.15)	

Table 8 (continued): Factor loadings of univariate and double sorted profitability- and value portfolios:

Panel B: Factor loadings of self-financing double sorted profitability and value portfolios

	Alpha	MKT	SMB	HML	UMD	RMW	CMA	BAB	QMJ	Adj R^2
GP and BM	0.383	-0.068	0.416	0.937		0.454	-0.038			22.5 %
	(1.76)	(-1.27)	(5.51)	(9.03)		(4.29)	(-0.24)			
	0.142	0.079	0.529	1.044	-0.055			-0.066	0.787	24.4 %
	(0.63)	(1.35)	(6.70)	(12.00)	(-1.04)			(-0.92)	(6.12)	
OP and BM	1.093	-0.082	-0.090	0.884		0.454	-0.270			10.0 %
	(3.39)	(-1.04)	(-0.82)	(5.85)		(2.94)	(-1.19)			
	0.722	0.060	-0.051	0.850	0.100			0.092	0.518	10.3 %
	(2.16)	(0.70)	(-0.43)	(6.59)	(1.27)			(0.86)	(2.75)	
CBOP and BM	0.854	-0.097	-0.164	0.807		0.307	0.221			16.6 %
	(3.21)	(-1.46)	(-1.78)	(6.35)		(2.37)	(1.17)			
	0.639	-0.020	-0.120	1.003	0.107			0.019	0.419	17.4 %
	(2.31)	(-0.28)	(-1.23)	(9.34)	(1.62)			(0.21)	(2.64)	
F-Score and BM	0.440	-0.193	0.063	0.770		0.424	0.299			36.1 %
	(2.61)	(-4.61)	(1.08)	(9.57)		(5.18)	(2.49)			
	0.179	-0.150	0.024	0.976	0.261			0.155	0.211	40.5 %
	(1.06)	(-3.38)	(0.40)	(14.82)	(6.44)			(2.84)	(2.17)	
ROCE and EBIT/EV	0.157	-0.041	0.095	0.200		1.393	0.208			50.2 %
	(1.26)	(-1.33)	(2.19)	(3.35)		(22.94)	(2.33)			
	-0.396	0.199	0.166	0.491	0.108			0.156	1.410	49.4 %
	(-3.01)	(5.81)	(3.58)	(9.62)	(3.44)			(3.68)	(18.71)	
GP and CBOP/EV	0.556	-0.119	0.195	-0.176		0.467	0.310			6.4 %
	(3.15)	(-2.71)	(3.18)	(-2.08)		(5.43)	(2.46)			
	0.204	0.050	0.340	0.167	0.079			-0.090	0.921	14.3 %
	(1.16)	(1.08)	(5.46)	(2.43)	(1.87)			(-1.59)	(9.09)	
OP and CBOP/EV	0.627	-0.112	-0.073	-0.205		0.712	0.421			17.6 %
	(3.84)	(-2.76)	(-1.28)	(-2.63)		(8.95)	(3.61)			
	0.134	0.084	0.021	0.283	0.343			-0.077	0.937	32.7 %
	(0.87)	(2.07)	(0.38)	(4.73)	(9.30)			(-1.55)	(10.58)	
CBOP and CBOP/EV	0.687	-0.128	-0.175	-0.061		0.461	0.360			22.1 %
	(5.31)	(-3.97)	(-3.90)	(-0.98)		(7.33)	(3.91)			
	0.316	0.013	-0.105	0.337	0.295			-0.075	0.644	37.3 %
	(2.61)	(0.41)	(-2.47)	(7.17)	(10.21)			(-1.92)	(9.27)	
CBOP_LCE and CBOP/EV	0.572	-0.045	-0.150	-0.123		0.406	0.433			15.8 %
	(4.53)	(-1.42)	(-3.41)	(-2.03)		(6.60)	(4.80)			
	0.290	0.076	-0.062	0.279	0.189			-0.093	0.661	25.7 %
	(2.34)	(2.34)	(-1.42)	(5.79)	(6.40)			(-2.33)	(9.30)	

Table 8 (continued): Factor loadings of univariate and double sorted profitability- and value portfolios:

Panel C: Factor loadings of long-only double sorted profitability and value portfolios

	Alpha	MKT	SMB	HML	UMD	RMW	CMA	BAB	QMJ	Adj R^2
GP and BM	-0.069	1.135	0.708	0.641		-0.185	-0.140			61.9 %
	(-0.37)	(24.26)	(10.84)	(7.13)		(-2.02)	(-1.05)			
	0.279	1.047	0.696	0.434	-0.337			-0.032	-0.204	65.6 %
	(1.49)	(21.47)	(10.58)	(5.99)	(-7.56)			(-0.53)	(-1.91)	
OP and BM	0.570	1.152	0.356	0.700		-0.349	-0.651			41.2 %
	(1.95)	(16.09)	(3.55)	(5.09)		(-2.49)	(-3.16)			
	0.873	1.059	0.276	0.235	-0.234			-0.021	-0.566	42.6 %
	(2.90)	(13.64)	(2.64)	(2.03)	(-3.29)			(-0.22)	(-3.34)	
CBOP and BM	0.233	1.179	0.266	0.515		-0.359	-0.156			45.3 %
	(0.95)	(19.21)	(3.10)	(4.37)		(-2.99)	(-0.89)			
	0.595	1.064	0.222	0.302	-0.234			-0.039	-0.463	47.3 %
	(2.35)	(16.10)	(2.49)	(3.08)	(-3.88)			(-0.48)	(-3.20)	
F-Score and BM	0.057	0.965	0.236	0.590		0.189	0.063			74.3 %
	(0.56)	(38.28)	(6.70)	(12.20)		(3.83)	(0.87)			
	0.131	0.941	0.212	0.559	-0.108			0.080	0.064	74.5 %
	(1.24)	(34.16)	(5.71)	(13.67)	(-4.29)			(2.35)	(1.06)	
ROCE and EBIT/EV	0.049	1.075	0.288	0.172		0.416	0.112			77.7 %
	(0.49)	(42.73)	(8.20)	(3.56)		(8.45)	(1.55)			
	0.070	1.101	0.315	0.196	-0.194			0.059	0.437	78.6 %
	(0.68)	(40.78)	(8.66)	(4.88)	(-7.87)			(1.76)	(7.37)	
GP and CBOP/EV	0.351	0.974	0.453	-0.002		-0.161	-0.052			69.1 %
	(2.62)	(29.22)	(9.74)	(-0.03)		(-2.47)	(-0.54)			
	0.505	0.962	0.508	-0.060	-0.220			-0.098	0.063	71.5 %
	(3.76)	(27.36)	(10.72)	(-1.16)	(-6.84)			(-2.27)	(0.82)	
OP and CBOP/EV	0.367	1.006	0.229	-0.012		-0.030	-0.004			73.3 %
	(3.24)	(35.64)	(5.80)	(-0.22)		(-0.54)	(-0.04)			
	0.424	1.025	0.258	0.057	-0.007			-0.160	0.083	74.0 %
	(3.62)	(33.53)	(6.27)	(1.25)	(-0.24)			(-4.25)	(1.24)	
CBOP and CBOP/EV	0.352	1.014	0.184	0.079		-0.003	-0.008			79.4 %
	(3.74)	(43.34)	(5.63)	(1.77)		(-0.06)	(-0.12)			
	0.436	1.018	0.201	0.114	-0.043			-0.120	0.057	80.1 %
	(4.52)	(40.33)	(5.90)	(3.05)	(-1.87)			(-3.87)	(1.03)	
CBOP_LCE and CBOP/EV	0.293	1.064	0.216	-0.011		-0.068	0.034			79.3 %
	(2.90)	(42.36)	(6.16)	(-0.24)		(-1.38)	(0.48)			
	0.449	1.051	0.253	0.007	-0.152			-0.126	0.077	81.2 %
	(4.47)	(40.05)	(7.16)	(0.19)	(-6.34)			(-3.92)	(1.33)	

Table 8 (continued): Factor loadings of univariate and double sorted profitability- and value portfolios:

Panel D: Factor loadings of short-only double sorted profitability and value portfolios

	Alpha	MKT	SMB	HML	UMD	RMW	CMA	BAB	QMJ	Adj R^2
GP and BM	-0.453	1.203	0.292	-0.296		-0.638	-0.102			75.0 %
	(-3.03)	(32.32)	(5.61)	(-4.15)		(-8.77)	(-0.96)			
	0.137	0.968	0.167	-0.610	-0.281			0.035	-0.992	80.8 %
	(1.00)	(27.06)	(3.47)	(-11.48)	(-8.61)			(0.79)	(-12.63)	
OP and BM	-0.493	1.221	0.458	-0.168		-0.808	-0.402			71.7 %
	(-2.76)	(27.47)	(7.38)	(-1.97)		(-9.30)	(-3.15)			
	0.194	0.993	0.344	-0.588	-0.324			-0.124	-1.095	78.2 %
	(1.18)	(23.19)	(5.96)	(-9.25)	(-8.27)			(-2.36)	(-11.66)	
CBOP and BM	-0.621	1.276	0.430	-0.292		-0.666	-0.377			80.3 %
	(-4.32)	(35.62)	(8.60)	(-4.25)		(-9.51)	(-3.67)			
	-0.045	1.083	0.342	-0.701	-0.341			-0.057	-0.882	85.8 %
	(-0.35)	(32.53)	(7.61)	(-14.17)	(-11.20)			(-1.40)	(-12.07)	
F-Score and BM	-0.384	1.158	0.173	-0.180		-0.236	-0.236			73.0 %
	(-2.72)	(32.99)	(3.53)	(-2.67)		(-3.43)	(-2.34)			
	-0.048	1.090	0.188	-0.416	-0.369			-0.075	-0.147	78.3 %
	(-0.37)	(31.63)	(4.05)	(-8.14)	(-11.71)			(-1.77)	(-1.94)	
ROCE and EBIT/EV	-0.108	1.116	0.193	-0.028		-0.978	-0.096			84.4 %
	(-1.03)	(42.64)	(5.28)	(-0.55)		(-19.10)	(-1.28)			
	0.466	0.902	0.149	-0.295	-0.302			-0.097	-0.973	88.8 %
	(5.01)	(37.13)	(4.56)	(-8.17)	(-13.61)			(-3.24)	(-18.25)	
GP and CBOP/EV	-0.205	1.093	0.258	0.174		-0.628	-0.362			77.2 %
	(-1.63)	(35.01)	(5.93)	(2.90)		(-10.28)	(-4.04)			
	0.301	0.912	0.168	-0.227	-0.298			-0.008	-0.858	83.7 %
	(2.72)	(31.55)	(4.32)	(-5.29)	(-11.30)			(-0.22)	(-13.52)	
OP and CBOP/EV	-0.260	1.119	0.301	0.193		-0.742	-0.425			80.6 %
	(-2.18)	(37.65)	(7.26)	(3.39)		(-12.77)	(-4.98)			
	0.290	0.941	0.238	-0.226	-0.349			-0.083	-0.854	87.8 %
	(2.93)	(36.45)	(6.83)	(-5.90)	(-14.81)			(-2.62)	(-15.06)	
CBOP and CBOP/EV	-0.335	1.142	0.359	0.140		-0.464	-0.368			85.9 %
	(-3.46)	(47.27)	(10.65)	(3.02)		(-9.82)	(-5.32)			
	0.120	1.005	0.306	-0.223	-0.338			-0.046	-0.587	92.5 %
	(1.63)	(52.17)	(11.78)	(-7.80)	(-19.22)			(-1.92)	(-13.87)	
CBOP_LCE and CBOP/EV	-0.280	1.108	0.366	0.111		-0.473	-0.399			84.5 %
	(-2.77)	(44.05)	(10.42)	(2.30)		(-9.62)	(-5.53)			
	0.159	0.976	0.315	-0.271	-0.342			-0.034	-0.584	91.0 %
	(1.98)	(46.42)	(11.13)	(-8.69)	(-17.79)			(-1.30)	(-12.67)	

Table 9: Persistence of profitability using z-scores:

This table reports the value-weighted average of profitability z-scores across stocks in the portfolio at the time of portfolio formation (t) up to ten years after portfolio formation (t+120M). Following Asness et. al. (2019), z-scores for each indicator measure (gross profitability, operating profitability, and cash-based operating profitability) are constructed by $z(x) = (r - \mu_r)/\sigma_r$, with r as the vector of ranks $r_i = rank(x_i)$, μ_r as the cross-sectional mean of r, and σ_r as the cross-sectional standard deviation of r. Correspondingly, each year at the end of June firms are ranked in ascending order based on their profitability z-scores and are subsequently assigned to a quintile portfolio which is constructed using NYSE breakpoints. The time series average of the value-weighted cross sectional means and their corresponding t-statistics are reported. Standard errors are adjusted for heteroskedasticity and autocorrelation with a Newey and West (1987) lag length of five years. Panel A considers the entire sample presented in Table 1, while Panel B and C recycle the z-scores of Panel A and exclusively focus on the highest B/M and CBOP/EV quintile portfolio firms, respectively.

Panel A: Persistence of profitability when considering value- and growth stocks collectively

Portfolio sort on GP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-1.31	-0.77	-0.17	0.51	1.26	2.56	208.05
	t+12M	-1.24	-0.71	-0.17	0.46	1.19	2.42	135.90
	t+60M	-1.08	-0.64	-0.22	0.37	1.05	2.13	80.69
	t+120M	-0.96	-0.54	-0.24	0.33	0.95	1.91	67.09
OP	t	-0.61	0.07	0.61	0.89	1.21	1.82	97.42
	t+12M	-0.50	0.12	0.59	0.84	1.15	1.65	74.21
	t+60M	-0.28	0.18	0.53	0.79	1.07	1.34	45.76
	t+120M	-0.15	0.27	0.49	0.77	0.99	1.15	39.64
CBOP	t	-0.34	0.25	0.64	0.82	1.08	1.42	82.20
	t+12M	-0.26	0.27	0.61	0.81	1.06	1.33	83.14
	t+60M	-0.11	0.30	0.55	0.79	1.03	1.14	53.52
	t+120M	-0.04	0.36	0.52	0.78	0.98	1.02	43.81

Portfolio sort on OP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-1.10	-0.80	-0.40	0.15	0.80	1.91	138.41
	t+12M	-0.99	-0.76	-0.37	0.15	0.73	1.72	92.17
	t+60M	-0.77	-0.68	-0.32	0.16	0.61	1.38	52.65
	t+120M	-0.63	-0.63	-0.25	0.18	0.54	1.17	36.85
OP	t	-0.98	-0.39	0.15	0.70	1.37	2.35	110.75
	t+12M	-0.75	-0.28	0.17	0.67	1.27	2.02	74.58
	t+60M	-0.31	-0.11	0.24	0.62	1.11	1.42	44.77
	t+120M	-0.08	-0.02	0.33	0.62	1.02	1.10	34.90
CBOP	t	-0.68	-0.17	0.25	0.65	1.28	1.96	102.02
	t+12M	-0.53	-0.12	0.27	0.65	1.23	1.76	89.10
	t+60M	-0.19	0.00	0.32	0.63	1.10	1.29	50.89
	t+120M	-0.02	0.07	0.39	0.64	1.02	1.04	38.47

Portfolio sort on CBOP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-0.57	-0.66	-0.44	-0.01	0.71	1.28	35.88
	t+12M	-0.56	-0.63	-0.41	0.00	0.67	1.23	40.09
	t+60M	-0.40	-0.58	-0.35	0.02	0.56	0.96	40.75
	t+120M	-0.29	-0.56	-0.27	0.07	0.49	0.78	29.74
OP	t	-0.51	-0.31	0.09	0.57	1.29	1.80	76.29
	t+12M	-0.44	-0.23	0.12	0.57	1.24	1.68	89.06
	t+60M	-0.10	-0.10	0.21	0.56	1.09	1.19	52.73
	t+120M	0.09	0.00	0.30	0.58	1.00	0.91	42.24
CBOP	t	-0.93	-0.33	0.20	0.72	1.38	2.31	115.73
	t+12M	-0.45	-0.15	0.21	0.64	1.23	1.68	70.44
	t+60M	-0.12	-0.02	0.29	0.63	1.10	1.23	48.86
	t+120M	0.07	0.07	0.36	0.63	1.02	0.95	39.29

Table 9 (continued): Persistence of profitability measures using z-scores

Panel B: Persistence of profitability of the highest B/M quintile portfolio firms

Portfolio sort on GP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-1.37	-0.92	-0.43	0.22	1.07	2.44	103.08
	t+12M	-1.33	-1.09	-0.83	-0.36	0.48	1.81	44.81
	t+60M	-1.12	-0.94	-0.66	-0.27	0.52	1.64	38.25
	t+120M	-1.00	-0.89	-0.56	-0.24	0.54	1.54	37.48
OP	t	-0.44	0.30	0.62	0.77	0.69	1.13	42.38
	t+12M	-0.77	-0.43	-0.26	-0.06	-0.11	0.65	27.48
	t+60M	-0.43	-0.21	-0.03	0.15	0.15	0.58	23.71
	t+120M	-0.24	-0.11	0.14	0.20	0.32	0.56	19.17
CBOP	t	-0.27	0.28	0.55	0.61	0.45	0.72	16.29
	t+12M	-0.52	-0.22	-0.07	0.01	-0.04	0.49	15.81
	t+60M	-0.27	-0.10	0.07	0.19	0.08	0.34	10.65
	t+120M	-0.16	-0.04	0.16	0.24	0.24	0.41	11.08

Portfolio sort on OP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-1.05	-0.86	-0.74	-0.48	0.08	1.13	43.83
	t+12M	-1.02	-0.98	-0.94	-0.79	-0.51	0.51	19.23
	t+60M	-0.71	-0.75	-0.83	-0.71	-0.38	0.33	9.51
	t+120M	-0.57	-0.65	-0.73	-0.67	-0.34	0.22	5.28
OP	t	-1.04	-0.40	0.15	0.63	1.27	2.31	126.58
	t+12M	-0.96	-0.75	-0.50	-0.28	0.15	1.11	35.88
	t+60M	-0.39	-0.33	-0.29	-0.09	0.25	0.64	19.12
	t+120M	-0.12	-0.11	-0.11	-0.02	0.31	0.42	9.69
CBOP	t	-0.71	-0.22	0.17	0.50	1.01	1.72	53.60
	t+12M	-0.70	-0.50	-0.32	-0.10	0.25	0.95	28.57
	t+60M	-0.29	-0.23	-0.18	-0.02	0.32	0.61	18.50
	t+120M	-0.10	-0.11	-0.04	0.06	0.33	0.43	10.59

Portfolio sort on CBOP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-0.69	-0.87	-0.68	-0.49	-0.05	0.64	13.91
	t+12M	-0.82	-1.00	-0.91	-0.80	-0.55	0.27	8.84
	t+60M	-0.62	-0.80	-0.78	-0.69	-0.42	0.20	6.65
	t+120M	-0.41	-0.70	-0.73	-0.65	-0.35	0.07	1.57
OP	t	-0.57	-0.29	0.19	0.57	1.05	1.62	41.26
	t+12M	-0.79	-0.71	-0.49	-0.29	0.07	0.86	25.56
	t+60M	-0.32	-0.37	-0.23	-0.06	0.18	0.50	19.65
	t+120M	0.03	-0.17	-0.14	0.01	0.30	0.27	7.13
CBOP	t	-1.00	-0.41	0.14	0.63	1.22	2.23	103.32
	t+12M	-0.61	-0.52	-0.30	-0.10	0.24	0.85	22.92
	t+60M	-0.26	-0.29	-0.13	0.04	0.27	0.53	17.99
	t+120M	0.00	-0.16	-0.10	0.11	0.33	0.32	7.69

Table 9 (continued): Persistence of profitability measures using z-scores

Panel C: Persistence of profitability of the highest CBOP/EV quintile portfolio firms

Portfolio sort on GP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-1.35	-0.83	-0.29	0.33	1.11	2.46	164.21
	t+12M	-0.96	-0.52	-0.13	0.30	1.01	1.97	99.31
	t+60M	-0.83	-0.41	-0.23	0.20	0.85	1.68	60.00
	t+120M	-0.74	-0.41	-0.29	0.15	0.69	1.43	38.83
OP	t	-0.58	0.19	0.64	0.82	0.95	1.53	55.81
	t+12M	-0.14	0.39	0.72	0.85	0.99	1.13	39.47
	t+60M	-0.05	0.46	0.57	0.76	0.90	0.95	27.48
	t+120M	0.05	0.38	0.50	0.70	0.81	0.76	18.46
CBOP	t	-0.45	0.07	0.50	0.69	0.79	1.24	30.88
	t+12M	0.08	0.51	0.76	0.87	0.98	0.90	25.98
	t+60M	0.08	0.54	0.62	0.76	0.87	0.80	21.52
	t+120M	0.13	0.46	0.54	0.72	0.80	0.67	14.78

Portfolio sort on OP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-1.08	-0.83	-0.52	-0.25	0.32	1.40	36.85
	t+12M	-0.69	-0.50	-0.28	-0.07	0.28	0.97	25.18
	t+60M	-0.46	-0.38	-0.17	-0.11	0.09	0.55	14.43
	t+120M	-0.40	-0.33	-0.12	-0.14	-0.01	0.38	8.84
OP	t	-1.16	-0.54	0.03	0.61	1.28	2.44	158.13
	t+12M	-0.58	-0.07	0.31	0.69	1.15	1.74	68.71
	t+60M	-0.18	0.14	0.40	0.60	0.91	1.09	30.70
	t+120M	-0.02	0.22	0.46	0.47	0.78	0.80	17.41
CBOP	t	-0.77	-0.49	-0.08	0.39	1.12	1.89	63.68
	t+12M	-0.34	0.11	0.43	0.77	1.15	1.49	49.82
	t+60M	-0.06	0.21	0.45	0.62	0.95	1.01	25.57
	t+120M	0.01	0.29	0.52	0.53	0.79	0.78	18.39

Portfolio sort on CBOP		P1	P2	P3	P4	P5	P5-P1	P5-P1 t-stat
GP	t	-0.93	-0.70	-0.46	-0.20	0.31	1.23	33.11
	t+12M	-0.62	-0.44	-0.23	-0.02	0.29	0.90	24.49
	t+60M	-0.47	-0.33	-0.18	-0.06	0.12	0.59	14.75
	t+120M	-0.43	-0.26	-0.19	-0.07	0.00	0.44	10.86
OP	t	-0.80	-0.25	0.20	0.63	1.17	1.97	81.44
	t+12M	-0.36	0.08	0.43	0.74	1.12	1.48	54.60
	t+60M	-0.05	0.25	0.44	0.62	0.91	0.96	25.90
	t+120M	0.10	0.32	0.43	0.56	0.75	0.64	16.46
CBOP	t	-1.07	-0.47	0.06	0.61	1.24	2.31	117.12
	t+12M	-0.17	0.28	0.52	0.80	1.11	1.28	35.43
	t+60M	0.04	0.33	0.49	0.64	0.93	0.89	21.62
	t+120M	0.17	0.39	0.49	0.58	0.76	0.60	14.78

Table 10: Fama and MacBeth (1973) regressions: Profitability and profitability growth

This table reports average Fama and MacBeth (1973) regression slopes from cross-sectional regressions that predict growth in profitability. The regressions are estimated using monthly data based on the sample described in Table 1. Regressions (1)-(3) test whether the lagged-assets-deflated profitability variables have predictive power for the growth in gross-, operating-, and cash-based operating profits on a one-year horizon, while regressions (4)-(6) and (7)-(9) report their predictive power for growth in profitability on a five-year and ten-year horizon, respectively. Panel A considers the entire sample presented in Table 1, while Panel B and C exclusively consider the highest B/M and CBOP/EV quintile portfolio firms, respectively. The natural logarithm of B/M, the natural logarithm of market capitalization, and the prior year returns are used as control variables. All independent variables are winsorized at the 1st and 99th percentiles and microcaps, which are defined as stocks with market values of equity below the 20th percentile of the NYSE market cap distribution, are excluded from this analysis. Test statistics are calculated using Newey and West standard errors, with zero, four, and nine lags, respectively.

Panel A: Predicting growth in profitability when considering value- and growth stocks collectively

	Regressions predicting one-year growth			Regressions predicting five-year growth			Regressions predicting ten-year growth		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regressions predicting gross profit growth: $y_t = \frac{GP_{t+\tau} - GP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0942			0.2929			0.4629		
	(14.60)			(7.33)			(5.04)		
OP		0.1188			0.3284			0.4964	
		(7.46)			(5.74)			(4.36)	
CBOP			0.0160			0.1684			0.2338
			(1.25)			(5.15)			(4.43)
Log(B/M)	-0.0396	-0.0478	-0.0578	-0.0813	-0.1145	-0.1357	-0.0906	-0.1489	-0.1856
	(-23.41)	(-23.71)	(-22.65)	(-16.02)	(-16.30)	(-13.09)	(-10.25)	(-21.25)	(-11.61)
Log(ME)	-0.0071	-0.0096	-0.0093	-0.0184	-0.0261	-0.0271	-0.0284	-0.0409	-0.0427
	(-10.50)	(-13.19)	(-12.19)	(-5.30)	(-8.59)	(-8.79)	(-3.42)	(-6.88)	(-7.86)
$r_{12,1}$	0.0881	0.0888	0.0915	0.1374	0.1432	0.1468	0.1167	0.1284	0.1344
	(22.97)	(22.57)	(21.77)	(17.29)	(15.84)	(15.79)	(10.31)	(9.09)	(9.02)
Regressions predicting operating profit growth: $y_t = \frac{OP_{t+\tau} - OP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0082			0.0203			0.0457		
	(2.76)			(1.84)			(2.62)		
OP		0.0162			0.0485			0.0977	
		(1.44)			(1.43)			(1.98)	
CBOP			0.0021			0.0539			0.0790
			(0.23)			(2.08)			(2.62)
Log(B/M)	-0.0260	-0.0260	-0.0275	-0.0543	-0.0536	-0.0554	-0.0625	-0.0623	-0.0677
	(-19.03)	(-19.25)	(-20.77)	(-16.72)	(-19.25)	(-16.02)	(-19.35)	(-17.71)	(-18.31)
Log(ME)	-0.0021	-0.0023	-0.0023	-0.0056	-0.0060	-0.0066	-0.0081	-0.0093	-0.0100
	(-4.11)	(-4.43)	(-4.29)	(-2.77)	(-3.17)	(-3.62)	(-1.65)	(-2.10)	(-2.36)
$r_{12,1}$	0.0711	0.0708	0.0711	0.0896	0.0890	0.0888	0.0725	0.0720	0.0721
	(24.24)	(24.60)	(24.36)	(19.37)	(19.97)	(19.82)	(12.39)	(12.84)	(12.52)
Regressions predicting cash-based operating profit growth: $y_t = \frac{CBOP_{t+\tau} - CBOP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0268			0.0409			0.0652		
	(7.14)			(3.89)			(4.50)		
OP		0.0770			0.1212			0.1672	
		(6.41)			(3.72)			(3.60)	
CBOP			-0.1903			-0.1337			-0.0733
			(-11.91)			(-5.56)			(-3.33)
Log(B/M)	-0.0160	-0.0141	-0.0345	-0.0507	-0.0472	-0.0695	-0.0600	-0.0570	-0.0809
	(-13.53)	(-9.28)	(-19.17)	(-19.59)	(-21.74)	(-17.84)	(-23.23)	(-22.35)	(-17.48)
Log(ME)	-0.0006	-0.0015	0.0008	-0.0052	-0.0063	-0.0045	-0.0079	-0.0097	-0.0087
	(-0.86)	(-2.14)	(1.12)	(-3.23)	(-4.49)	(-2.65)	(-1.75)	(-2.31)	(-2.04)
$r_{12,1}$	0.0412	0.0408	0.0498	0.0708	0.0701	0.0784	0.0605	0.0594	0.0669
	(12.64)	(12.38)	(15.71)	(12.85)	(13.08)	(18.03)	(10.74)	(10.36)	(12.17)

Panel B: Predicting growth in profitability for the highest B/M quintile portfolio firms									
	Regressions predicting one-year growth			Regressions predicting five-year growth			Regressions predicting ten-year growth		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regressions predicting gross profit growth: $y_t = \frac{GP_{t+\tau} - GP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0132			0.0193			0.1320		
	(1.34)			(0.37)			(1.38)		
OP		-0.1209			-0.1168			-0.0496	
		(-5.44)			(-1.65)			(-0.31)	
CBOP			-0.1149			-0.1199			-0.1071
			(-7.87)			(-2.45)			(-1.32)
Log(B/M)	-0.0282	-0.0409	-0.0393	-0.0795	-0.0976	-0.0970	-0.0890	-0.1259	-0.1315
	(-8.78)	(-9.69)	(-9.75)	(-5.79)	(-7.73)	(-7.06)	(-5.25)	(-10.73)	(-8.87)
Log(ME)	-0.0018	-0.0026	-0.0022	-0.0111	-0.0131	-0.0136	-0.0174	-0.0242	-0.0236
	(-3.26)	(-3.97)	(-3.36)	(-5.53)	(-4.50)	(-4.50)	(-2.74)	(-4.42)	(-4.20)
$r_{12,1}$	0.0532	0.0541	0.0547	0.0884	0.0929	0.0927	0.0730	0.0721	0.0742
	(9.62)	(9.95)	(9.93)	(10.10)	(9.76)	(9.70)	(5.09)	(4.34)	(4.60)
Regressions predicting operating profit growth: $y_t = \frac{OP_{t+\tau} - OP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	-0.0253			-0.0661			-0.0701		
	(-5.10)			(-4.51)			(-2.79)		
OP		-0.1654			-0.2623			-0.2150	
		(-8.69)			(-5.23)			(-2.64)	
CBOP			-0.0985			-0.1581			-0.1243
			(-8.02)			(-3.84)			(-2.38)
Log(B/M)	-0.0194	-0.0266	-0.0216	-0.0428	-0.0475	-0.0381	-0.0460	-0.0465	-0.0402
	(-8.98)	(-8.35)	(-7.52)	(-8.76)	(-9.29)	(-7.20)	(-6.03)	(-8.46)	(-6.25)
Log(ME)	-0.0011	-0.0001	0.0001	-0.0067	-0.0043	-0.0044	-0.0082	-0.0063	-0.0062
	(-2.68)	(-0.11)	(0.19)	(-5.03)	(-3.11)	(-3.11)	(-2.08)	(-1.73)	(-1.64)
$r_{12,1}$	0.0429	0.0440	0.0436	0.0483	0.0525	0.0511	0.0419	0.0432	0.0440
	(11.74)	(12.17)	(12.15)	(13.01)	(13.43)	(13.49)	(5.75)	(5.23)	(5.55)
Regressions predicting cash-based operating profit growth: $y_t = \frac{CBOP_{t+\tau} - CBOP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0019			-0.0444			-0.0523		
	(0.29)			(-2.81)			(-1.89)		
OP		-0.0713			-0.1711			-0.1211	
		(-2.68)			(-3.02)			(-1.57)	
CBOP			-0.4316			-0.4983			-0.4231
			(-17.40)			(-11.33)			(-10.66)
Log(B/M)	-0.0060	-0.0108	-0.0297	-0.0393	-0.0409	-0.0540	-0.0520	-0.0498	-0.0647
	(-1.63)	(-2.57)	(-6.32)	(-8.15)	(-7.10)	(-8.47)	(-5.77)	(-6.96)	(-8.11)
Log(ME)	-0.0000	-0.0002	0.0013	-0.0041	-0.0025	-0.0010	-0.0066	-0.0056	-0.0040
	(-0.06)	(-0.19)	(1.75)	(-4.10)	(-2.31)	(-0.99)	(-1.64)	(-1.47)	(-1.08)
$r_{12,1}$	0.0214	0.0215	0.0287	0.0344	0.0372	0.0452	0.0415	0.0411	0.0474
	(5.61)	(5.80)	(7.12)	(9.35)	(8.16)	(13.77)	(5.50)	(4.84)	(6.14)

Panel C: Predicting growth in profitability for the highest CBOP/EV quintile portfolio firms

	Regressions predicting one-year growth			Regressions predicting five-year growth			Regressions predicting ten-year growth		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regressions predicting gross profit growth: $y_t = \frac{GP_{t+\tau} - GP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0503			0.2505			0.4622		
	(5.52)			(4.96)			(5.12)		
OP		-0.0066			0.0698			0.1020	
		(-0.29)			(1.05)			(0.63)	
CBOP			-0.0093			0.0289			-0.0261
			(-0.40)			(0.35)			(-0.12)
Log(B/M)	-0.0230	-0.0362	-0.0362	-0.0648	-0.1186	-0.1208	-0.0728	-0.1736	-0.1844
	(-9.18)	(-9.51)	(-9.38)	(-6.34)	(-5.98)	(-5.87)	(-3.67)	(-4.32)	(-4.04)
Log(ME)	-0.0032	-0.0051	-0.0050	-0.0176	-0.0267	-0.0267	-0.0312	-0.0485	-0.0484
	(-4.32)	(-5.70)	(-5.56)	(-5.86)	(-8.43)	(-8.09)	(-5.88)	(-14.44)	(-13.28)
$r_{12,1}$	0.0824	0.0850	0.0854	0.1416	0.1506	0.1526	0.1128	0.1248	0.1293
	(19.32)	(19.86)	(19.48)	(14.32)	(12.24)	(12.16)	(9.59)	(6.82)	(7.00)
Regressions predicting operating profit growth: $y_t = \frac{OP_{t+\tau} - OP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0030			0.0347			0.0724		
	(0.24)			(2.11)			(3.06)		
OP		-0.0825			-0.0227			0.0279	
		(-2.75)			(-0.64)			(0.33)	
CBOP			-0.0536			0.0232			0.0659
			(-2.03)			(0.68)			(0.87)
Log(B/M)	-0.0119	-0.0213	-0.0185	-0.0431	-0.0537	-0.0480	-0.0538	-0.0651	-0.0603
	(-1.71)	(-4.55)	(-3.83)	(-5.96)	(-5.68)	(-5.37)	(-3.32)	(-3.55)	(-3.35)
Log(ME)	0.0000	-0.0001	-0.0002	-0.0062	-0.0075	-0.0075	-0.0125	-0.0150	-0.0148
	(0.17)	(-0.13)	(-0.16)	(-3.05)	(-3.63)	(-3.67)	(-3.11)	(-3.78)	(-3.84)
$r_{12,1}$	0.0691	0.0712	0.0706	0.0906	0.0917	0.0910	0.0665	0.0668	0.0666
	(19.77)	(18.89)	(19.14)	(20.27)	(17.70)	(17.27)	(11.50)	(11.23)	(12.10)
Regressions predicting cash-based operating profit growth: $y_t = \frac{CBOP_{t+\tau} - CBOP_t}{AT_{t+\tau-1} + AT_{t-1}}$									
GP	0.0495			0.0829			0.1235		
	(3.61)			(4.44)			(5.64)		
OP		0.1105			0.1693			0.2234	
		(3.14)			(4.23)			(2.98)	
CBOP			-0.2168			-0.1454			-0.0473
			(-6.33)			(-2.69)			(-0.53)
Log(B/M)	0.0167	0.0199	-0.0168	-0.0219	-0.0210	-0.0559	-0.0338	-0.0340	-0.0639
	(2.20)	(3.55)	(-2.87)	(-3.16)	(-2.83)	(-5.36)	(-2.55)	(-2.64)	(-3.88)
Log(ME)	0.0094	0.0074	0.0068	0.0014	-0.0019	-0.0019	-0.0054	-0.0101	-0.0098
	(5.60)	(5.83)	(5.53)	(0.86)	(-1.22)	(-0.97)	(-1.50)	(-2.73)	(-2.57)
$r_{12,1}$	0.0583	0.0589	0.0646	0.0832	0.0833	0.0907	0.0744	0.0722	0.0784
	(12.54)	(11.84)	(13.17)	(15.32)	(13.64)	(14.94)	(12.06)	(9.59)	(10.60)

APPENDIX: A1: Variable definitions:

The accounting variables used in this thesis are obtained from Compustat and the closing date of the accounting year is lagged by six months to avoid look-ahead bias. The constructed measures are the following:

Deflators for profitability:

Lagged book value of assets: Lagged assets are defined as last year's book value of assets (AT)

Lagged capital employed: Lagged capital employed is last year's capital employed being defined as net working capital plus net fixed assets which is current assets (ACT) minus cash and short-term investment (CHE) minus current liabilities (LCT) plus debt in current liabilities (DLC) plus property, plant, and equipment, when available. If capital employed is still missing it is defined as assets (AT) minus current liabilities (LCT) plus debt in current liabilities (DLC) minus other intangible assets, when available. If the value is still missing, capital employed is set equal to invested capital which is defined as book value of equity plus debt (DLC+DLTT) minus other intangible assets, or if missing, as working capital (WCAP) plus property, plant, and equipment (PPEGT).

Profitability measures:

Gross profitability (GP): Gross profits are defined in line with Novy-Marx (2013) as revenues (REVT) minus cost of goods sold (COGS).

Operating profitability (OP): In this study, operating profits are calculated using the definition of Ball et al. (2016) who define it as revenues (REVT) minus cost of goods sold (COGS) and, when available, minus reported sales, general, and administrative expenses, whereby the latter expenses are adjusted for expenditures on research and development (XSGA -XRD).

Cash-based operating profitability (CBOP): Operating profits are converted to a cash basis by adding or subtracting changes in balance sheet items as proposed by Ball et al. (2016). Correspondingly, cash-based operating profitability is defined as operating profitability minus the change in accounts receivable (RECT) minus the change in inventory (INVT) minus the change in prepaid expenses (XPP) plus the change in deferred revenue (DRC+DRLT) plus the change in trade accounts payable (AP) plus the change in accrued expenses (XACC). In case that balance sheet values are missing, the corresponding missing change is set to zero for the computation of cash-based operating profitability. If the cash-based operating measure is still missing, an alternative calculation based on cash flow statement accruals is used to calculate cash-based operating profitability. Correspondingly, cash-based operating profitability is operating profitability plus a decrease in accounts receivable (RECCH) plus a decrease in inventory (INVCH) plus an increase in accounts payable and accrued liabilities (APALCH).

ROCE: Return on capital employed is defined as earnings before interest and taxes (EBIT) or, if missing, operating income (OIADP) divided by contemporaneous capital employed.

Accruals: Accruals are calculated using the balance sheet approach of Sloan (1996), if balance sheet values are available, or else, following the cash flow approach as presented by Ball et al. (2016). In case that individual balance sheet values are missing, the corresponding missing change is replaced with zero. In detail, accruals are defined either as:

Accruals ≡ Δ (Current assets (ACT)) − Δ (Cash (CH)) − [Δ (Current liabilities (LCT)) − Δ (Debt in current liabilities (DLC)) − Δ (Income taxes payable (TXP))] − Depreciation (DP) or, if missing, as:

Accruals = −Decrease in accounts receivable (RECCH) − Decrease in Inventory (INVCH) − Increase in accounts payable and accrued liabilities (APALCH) − Net change in other asset and liabilities (AOLOCH) − Increase in accrued income taxes (TXACH)

F-Score: F-Score is a composite measure and is calculated according to the definition of Piotroski (2000). It simultaneously considers the profitability, financial leverage/liquidity, and operating efficiency dimension and is constructed as the sum of the following nine binary variables:

F-Score = $F_{ROA} + F_{CFO} + F_{\Delta ROA} + F_{ACCRUAL} + F_{\Delta Lever} + F_{\Delta Liquid} + F_{EQ\_OFFER} + F_{\Delta Margin} + F_{\Delta Turnover}$ whereby:

Profitability indicator measures equal one if they are above zero:

F_{ROA}: Net income before extraordinary items (IB) scaled by lagged assets (AT)
F_{CFO}: Operating cash flow (OANCF) or, if not available, (NI + DP – WCAPCH), scaled by lagged assets (AT)
$F_{\Delta ROA}$: $ROA_t - ROA_{t-1}$
$F_{ACCRUAL}$: $CFO_t - ROA_t$ scaled by lagged total assets (AT)

Financial performance: $F_{\Delta Liquid}$ is equal to one if the change is greater than zero; otherwise a positive change indicates weakness, and the indicator measure is set to zero:

$F_{\Delta Lever}$: Long-term debt (DLTT) scaled by average of assets and lagged assets (AT) – last year's (Long-term debt (DLTT) scaled by average of assets and lagged assets (AT))
$F_{\Delta Liquid}$: Current assets (ACT) / Current liabilities (LCT) – last year's (Current assets (ACT) / Current liabilities (LCT))
F_{EQ_OFFER}: Sale of common and preferred stock (SSTK)

Operating efficiency indicator measures equal one if they are above zero:

$F_{\Delta Margin}$: (SALE minus COGS) scaled by SALE – last year's ((SALE minus COGS) scaled by SALE)
$F_{\Delta Turnover}$: SALE/AT – last year's SALE/AT

Valuation measures:

B/M: Book-to-market is defined as book equity scaled by market capitalization, whereby the usual lag in accounting measures of six months is used to avoid taking unintentional positions in momentum. The book value of equity is defined as shareholder equity plus deferred taxes (TXDITC) minus preferred stock (PSTKR or PSTKRV or PSTKL or PSTK), when available. Shareholder equity (SEQ) is used when available, or else common equity (CEQ) plus preferred stock (PSTK or PSTKRV). If still missing, shareholder equity is defined as total assets (AT) minus total liabilities (LT). The market value of equity is defined as a stock's fiscal year closing price (PRCC_F) multiplied with its common shares outstanding (CSHO).

EBIT/EV: This inverse enterprise multiple is defined as earnings before interest and taxes (EBIT) or, if missing, operating income (OIADP), divided by the sum of the market value of equity (PRCC_F*CSHO) plus prior year's total debt (DLC+DLTT) plus preferred stock value (PSTKRV) minus cash and short-term investment (CHE), when available.

CBOP/EV: This inverse enterprise multiple is defined as cash-based operating profitability divided by enterprise value, whereby the latter is also defined as the sum of the market value of equity (PRCC_F*CSHO) plus prior year's total debt (DLC+DLTT) plus preferred stock value (PSTKRV) minus cash and short-term investment (CHE), when available.

Appendix A2: Deflator choice for profitability and the cross-section of returns

The aim of this section of the Appendix is to critically reflect on deflator choice and to incrementally add to the findings of Ball et al. (2015) and Hou et al. (2020). This study extents their research by considering cash-based operating profitability as an alternative profitability measure and lagged capital employed as a novel deflator choice. Hence, to compare the explanatory power of gross-, operating-, and cash-based operating profits for the cross-section of return in this study, book value of assets, lagged book value of assets, and lagged capital employed are used as deflators. While the mean profitability is on average higher when using lagged capital employed instead of lagged assets as a deflator for profitability, the corresponding standard deviations of the scaled profitability measures increase considerably too (reported in Table A1). As a result, the distributions of the lagged-capital-employed-deflated profitability variables exhibit a positive excess kurtosis and are correspondingly leptokurtic. While the Spearman rank correlations among the lagged-capital-employed and lagged-assets-deflated profitability measures are strongly positive, Pearson correlations (not reported) are only moderately positive. This discrepancy indicates that the relationship between the variables is monotonic, but not necessarily linear.

The correlations between the profitability measures and the one-month ahead returns are weakly positive and further attenuated when using lagged book value of assets and lagged capital employed instead of the book value of assets as a deflator for the profitability variables. Collectively, these findings suggest that deflator choice not only affects the properties of the constructed profitability measures, but it evidently also affects their predictive power for the cross-section of returns as documented by Hou et al. (2020). This hypothesis is tested with Fama and MacBeth (1973) regressions which use the same control variables as in the main analysis presented in Table 3. The corresponding results are presented in Table A2. Consistent with the findings of Hou et al. (2020), all considered profitability measures have the strongest predictive power for expected monthly returns when scaled by contemporaneous book value of assets. Although gross-, operating-, and cash-based operating profits maintain their economically and statistically significant predictive power for expected monthly returns at a 5 % significance level when deflated by lagged assets, the coefficients on operating profitability and gross profitability are almost halved compared to the ones when using contemporaneous assets as a deflator. In line with the conclusion of Hou et al. (2020) that the gross profitability premium is confounded with the investment premium when using contemporaneous assets, the factor loading on the CMA factor that is reported in Panel A of Table 6 is highly negative for univariate zero-cost portfolios formed on lagged-assets-deflated operating- and gross profitability. Meanwhile, the CMA factor loading is positive for the zero-cost portfolio sorted on lagged-assets-deflated cash-based operating profitability when considering a Fama and French (2015) five-factor regression. Collectively, these findings underline the evidence of Hou et al. (2020) which suggests that purging the investment premium leads to an attenuated gross profitability premium.

However, when it comes to a direct comparison between using lagged assets and lagged capital employed as a deflator for profitability, it is less obvious whether the former leads to a stronger predictive power for all profitability measures. Nonetheless, not only is gross profitability scaled by lagged capital employed a barely statistically significant predictor of monthly returns at a 5 % significance level, but also is a one-standard deviation change in operating- and cash-based operating profitability ceteris paribus associated with a lower increase in expected monthly returns. (0.15 and 0.25 percentage points, respectively) Collectively these findings complement the evidence of Ball et al. (2015) and point to a general superior predictive power of profitability measures for the cross-section of returns when using lagged assets instead of lagged capital employed. Moreover, the evidence accentuates a particularly strong predictive power of cash-based operating profitability for expected returns and emphasizes that the main findings of this thesis persist when using lagged capital employed as an alternative deflator for profitability.

Table A1: Descriptive statistics

This table presents in Panel A the distributions of the time-series average of the cross-sectional means and cross-sectional standard deviations together with the time series averages of the percentiles of the relevant profitability variables. The profitability measures gross profitability (GP), operating profitability (OP), and cash-based operating profitability (CBOP) are either scaled by contemporaneous assets (A), lagged assets (LA), or lagged capital employed (LCE). Panel B presents the Spearman rank correlations of the variables of interest. The sample period starts in July 1963 and ends in November 2019. This study includes all firms traded on NYSE, AMEX, and NASDAQ, and excludes securities other than ordinary common shares. Firms are required to have non-missing values for the following items: market value of equity, book-to-market, gross profit, and book value of total assets. Financial firms, defined as firms with one-digit SIC codes of six, are excluded from this analysis. The time-series averages of the cross-sectional means and standard deviations of the accounting variables are reported after the according profitability measures have been winsorized at the 1st and 99th percentile.

Panel A: Distributions

			Percentiles				
Variable	Mean	SD	1st	25th	50th	75th	99th
Profitability measures deflated by contemporaneous assets							
Gross profitability (GP)	0.360	0.289	-0.541	0.176	0.333	0.512	1.254
Operating profitability (OP)	0.116	0.164	-0.625	0.068	0.133	0.201	0.480
Cash-based operating profitability (CBOP)	0.105	0.171	-0.639	0.046	0.122	0.195	0.514
Profitability measures deflated by lagged capital employed							
Gross profitability (GP)	0.803	2.120	-9.152	0.236	0.523	1.004	12.757
Operating profitability (OP)	0.269	1.230	-6.200	0.096	0.195	0.365	6.897
Cash-based operating profitability (CBOP)	0.220	1.304	-6.183	0.063	0.156	0.308	6.438

Panel B: Spearman variable rank correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) r_{1f}	-									
(2) GP_A	0.021	-								
(3) GP_LA	0.017	0.940	-							
(4) GP_LCE	0.017	0.709	0.747	-						
(5) OP_A	0.008	0.526	0.553	0.358	-					
(6) OP_LA	0.050	0.483	0.593	0.392	0.950	-				
(7) OP_LCE	0.043	0.402	0.491	0.651	0.714	0.754	-			
(8) CBOP_A	0.033	0.408	0.358	0.211	0.773	0.677	0.492	-		
(9) CBOP_LA	0.049	0.395	0.409	0.250	0.796	0.763	0.558	0.963	-	
(10) CBOP_LCE	0.047	0.333	0.336	0.493	0.609	0.578	0.781	0.750	0.776	-

Table A2: Profitability in Fama and MacBeth (1973) regressions depending on deflator choice:

This table reports average Fama and MacBeth (1973) regression slopes (multiplied by 100) from cross-sectional regressions that predict monthly returns. Their corresponding t-values are presented in parenthesis. The regressions are estimated using monthly data based on the sample described in Table 1. For the profitability measures in regressions (1)-(3) contemporaneous book value of assets are used as a deflator, while in regressions (4)-(6) and (7)-(9) lagged assets and lagged capital employed are used to scale the considered profitability variables, respectively. The natural logarithm of B/M, the natural logarithm of market capitalization, and the prior month as well as prior 12-month period excluding month t-1 returns are used as control variables. All independent variables are winsorized at the 1st and 99th percentiles and microcaps, which are defined as stocks with market values of equity below the 20th percentile of the NYSE market cap distribution, are excluded from this analysis.

	Accounting variables deflated by								
	Total assets			Lagged total assets			Lagged capital employed		
Regressor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GP	0.7203 (5.21)			0.3633 (3.32)			0.0499 (1.97)		
OP		2.7263 (8.57)			1.3803 (5.84)			0.1180 (2.41)	
CBOP			2.6109 (10.60)			1.8253 (9.57)			0.1899 (4.55)
Log(B/M)	0.2744 (3.97)	0.3413 (4.91)	0.2947 (4.29)	0.2564 (3.81)	0.3046 (4.55)	0.2974 (4.36)	0.2070 (3.21)	0.2103 (3.24)	0.2118 (3.22)
Log(ME)	-0.0296 (-0.81)	-0.0549 (-1.53)	-0.0650 (-1.83)	-0.0304 (-0.84)	-0.0425 (-1.18)	-0.0582 (-1.63)	-0.0324 (-0.90)	-0.0332 (-0.92)	-0.0363 (-1.00)
$r_{1,1}$	-3.7447 (-8.88)	-3.7130 (-8.79)	-3.7304 (-8.82)	-3.6891 (-8.73)	-3.6369 (-8.59)	-3.6836 (-8.70)	-3.6094 (-8.49)	-3.5715 (-8.39)	-3.5959 (-8.45)
$r_{12,2}$	0.6411 (3.20)	0.6209 (3.12)	0.5943 (2.98)	0.6585 (3.29)	0.6484 (3.24)	0.6045 (3.02)	0.6665 (3.31)	0.6631 (3.29)	0.6598 (3.28)
Observations		858,427			854,118			853,388	
R-Squared	0.2654	0.2649	0.2641	0.2655	0.2651	0.2646	0.2633	0.2633	0.2632