

Erasmus University Rotterdam

ERASMUS SCHOOL OF ECONOMICS

Supervisor: Dr. Ricardo Barahona

The impact of mispricing on cross-sectional stock market anomalies

Abstract

Cross-sectional equity market anomalies have long been in the focus of asset pricing and behavioural finance literature. The scientific discourse has largely focused on whether these anomalies are the representation of risk premia on some underlying risk source or cannot be explained by risk sources but effectively with investor behaviour and market sentiment. The results of this paper imply that while for specific anomalies and periods, specific mispricing factors can improve the explanatory power of risk factor models, there seems to be no single universal effect of mispricing in all anomalies and these anomalies are generally robust to removing highly mispriced stocks from the asset space. In the case of most anomalies, defining the estimation period matters more for the significance of the anomaly, implying that they do not represent trading opportunities or a consistent risk premia, but cannot be accommodated by one catch-all mispricing factor.

Keywords: JEL C33, G12, G14, G4

Author:
David Gyarakı

Student ID:
582340

November 22, 2021

Contents

1	Introduction	1
2	Previous literature	1
2.1	Asset pricing	1
2.2	Mispricing in asset pricing context	2
2.3	Examined anomalies	3
3	Initial hypotheses	5
4	Methodology	6
4.1	Mispricing measures	7
4.2	Construction of anomaly dependent variables	8
4.3	Factor formulation	9
5	Results	11
5.1	Anomalies with traditional factor models	11
5.1.1	Anomalies explained by CAPM	11
5.1.2	Anomalies explained by FF3	13
5.1.3	Anomalies explained by FF5	14
5.2	Augmenting factor models with mispricing factors	14
5.2.1	Augmenting with the SY-factor	14
5.2.2	Augmenting with the BG-factor and its alternative	15
5.3	Decade-wise analysis of anomalies	16
5.3.1	Periodical estimation by factor models	17
5.3.2	A word on the alpha patterns	19
5.3.3	Periodical estimation by augmented factor models	21
5.4	GRS-test results for hedge portfolios only	23
5.5	Anomalies in the fair-valued universe of stocks	24
5.6	Mispricing as an anomaly itself	26
5.7	Reconciliation of findings with previous literature	28
6	Conclusion	29
7	Appendix	31
7.1	Appendix A: The construction of mispricing measures	31
7.1.1	Bartram and Grinblatt (2018) variables	31
7.1.2	Stambaugh and Yuan (2017) variables	32
7.1.3	Bartram and Grinblatt variables with a simulation approach	35
7.2	Appendix B: Result outputs	36

1 Introduction

The aim of this research is to investigate the effects of mispricing on stock returns and anomaly persistence for a selected set of well-known anomalies when accounted for mispricing. While a large number of cross-sectional return anomalies have been identified by academic research, the interaction of these anomalies is sometimes overlooked. As [Stambaugh & Yuan \(2017\)](#) points out, many of these anomalies might be partially explained by mispricing effects. Furthermore, as [Bartram & Grinblatt \(2018\)](#) points out, mispricing could itself be a cross-sectional anomaly as well. If mispricing is considered as an anomaly itself, provided that mispricing anomaly can explain other cross-sectional anomalies, these anomalies might be considered as proxies or repackaged versions of the mispricing anomaly.

The main research question of the paper revolves around the connection of anomalies and mispricing. What is the impact of mispricing on cross-sectional anomalies of equity prices? Can a mispricing-based factor model explain the cross-sectional returns of equities? Besides, the question arises that if mispricing impacts stock-market anomalies, can it price the anomaly portfolio returns more effectively than traditional risk factor models? After investigating the explanatory power of mispricing factors on anomalies however, comes the question of persistence. While an alpha-decay investigation can be carried out with the help of the factor models, persistence has another dimension than time in that case. The question of robustness arises regarding the persistence of anomalies even if the mispricing component is mitigated or completely isolated. By removing highly mispriced stocks from the asset space before constructing portfolios for the cross-sectional anomaly analysis, one expects to see relatively similar results for the explanatory power of factor models for that particular anomaly even after removing mispriced stocks. If an anomaly has a risk-based explanation behind it, in theory the results should be similar, provided that the removal of mispriced stocks does not significantly alter the characteristics of the asset space.

The structure of the paper follows as: Section 2 presents a non-exhaustive overview on previous literature on the role of mispricing in asset pricing and the investigated anomalies. Section 3 briefly discusses the initial expectations and tested hypotheses of the paper. Section 4 provides a brief description of the methodology with more details in Section 7.1. Section 5 presents and interprets the results of the paper as well as providing some potential explanation into the discrepancies of the findings with previous research and some avenues for future research. Finally, Section 6 concludes.

2 Previous literature

2.1 Asset pricing

Asset pricing models generally rely upon the concept that returns and asset prices are explained by the risk exposure of the assets. Perhaps one of the most famous of these models was introduced by [Sharpe \(1964\)](#) in the form of the Capital Asset Pricing Model (CAPM), proposing that this risk exposure is identical to the market risk for all assets. A more generalised approach was introduced by [Ross \(1976\)](#) in the form of the Arbitrage Pricing Theory (APT), which suggests that asset prices are explained by risk sources but relaxes the assumption that this risk would only be composed of market risk. Based upon this, numerous asset pricing models were proposed, such as [Fama & French \(1993\)](#), [Fama](#)

& French (2015) or Hou et al. (2015), which models aim to incorporate other risk sources relevant for asset pricing.

When it comes to equity markets, cross-sectional anomalies present puzzling challenges to these asset pricing models. Nevertheless, a long list of anomalies have been investigated and identified by previous research. These anomalies present important challenges to investment strategies but potentially provide opportunities as well. Furthermore, if anomalies cannot be explained by some risk factor efficiently, they present serious challenges to the APT and risk-based asset pricing factor models. Hence, a significant part of the literature focuses on how to reconcile the existence of cross-sectional anomalies within asset pricing and to find the most appropriate asset pricing model to fully explain returns and capture all potentially significant Jensen's alpha measures (Jensen, 1969). However, asset pricing models are only as good as the factors used in the model and their risk-based explanations, which gives concern to the level of accuracy these factors are proxied for (Roll, 1977).

Beyond the difficulties of correctly specifying and testing asset pricing models, issues might arise regarding the model's relevance. While the assumption that asset pricing models can correctly price assets or measure alphas may be tested by different tools, such as the GRS-test (Gibbons et al., 1989), the real economic significance of the measured alphas is not established. Van Binsbergen & Opp (2019) argue, that simply measuring the magnitude of alphas and using these measurements for further testing, such as the GRS-test, might establish the importance of the anomaly for investors, but shows an incomplete picture of the anomaly's effect and significance on the real economy. Hence, Van Binsbergen & Opp (2019) emphasise the need to consider the persistence of anomalies beyond measuring the magnitude and significance of anomalies in order to assess the importance of anomalies from the perspective of financial markets.

2.2 Mispricing in asset pricing context

The issue of mispricing and cross-sectional anomalies motivated a large scope of papers in the literature, which this paper cannot possibly all cover and summarize. As mentioned before, Bartram & Grinblatt (2018, 2021) suggest that a strategy based on mispricing can generate significant and persistent alphas on the cross-section of equities. However, most papers tend to focus on the explanatory side of the puzzle, namely whether mispricing can help explaining anomaly returns. A previously mentioned model has been proposed by Stambaugh & Yuan (2017), where mispricing augments the Fama-French three factor model and can be proxied by one overall, or two factors based on management-related and performance-related anomalies linked to mispricing.

Furthermore, some other models have been proposed for using different proxies to construct a mispricing factor and use it in a factor-model explaining cross-sectional anomalies. Hirshleifer & Jiang (2010) propose a UMO (undervalued-minus-overvalued) factor based on repurchase and new issue stock portfolios, and provide evidence that this factor is quite powerful in explaining a series of anomalies and cannot be itself explained by other risk factors. The advantage of this factor is that mispricing is considered systematic, hence the model is slightly more flexible than the previous approaches. This concept has been investigated further by Walkshäusl (2016) who finds further evidence that the UMO-factor bears strong explanatory power in cross-sectional model settings and it can poorly be substituted or explained by any of the five Fama-French factors (Fama & French, 2015). Furthermore, he also suggests to use a factor model without any

other factors than market returns and the mispricing factor, and finds it similar to the FF5 model, albeit with poor performance in explaining cross-sectional anomalies.

Besides the model proposed by [Stambaugh & Yuan \(2017\)](#), [Daniel et al. \(2020\)](#) introduce a model with mispricing attributed to investor behaviour and distinguish between short-term and long-term mispricing. Furthermore, the authors' model also uses only the mispricing factors along with market returns. This list of papers present evidence that mispricing can be a strong explanatory factor without a strong risk-based explanation behind it. Consequently, if mispricing is a good explanatory factor to cross-sectional anomalies, the question presents itself whether these anomalies are persistent if mispricing is out of the picture.

2.3 Examined anomalies

This paper employs mispricing identification techniques from the literature to establish asset pricing factors for mispricing and investigate their effectiveness in factor models. These factor models and their augmented versions with mispricing are bench-marked on their ability to explain a set of well-known cross-sectional anomalies. These anomalies are the size, book-to-market, investment, profitability, momentum and dividend yield anomalies. In the following, I aim to create a non-exhaustive review of literature previously published on these anomalies.

The size anomaly was first documented by [Banz \(1981\)](#), who finds that small market capitalization firms generate higher risk-adjusted returns compared to large firms on average. While the size anomaly started out as a puzzle for portfolio returns and a challenge to CAPM, since then it has become one of the most investigated anomalies and many have tried to reconcile its existence with CAPM. Famously, [Fama & French \(1993\)](#) argued that the size anomaly is a result of a source of risk priced in the portfolio returns other than market risk and constructed the size factor as a risk factor to explain returns. Many risk-factor models have been developed, which include a size-related factor, such as [Hou et al. \(2015\)](#) or the five-factor model of [Fama & French \(2015\)](#). Hence, the size anomaly is perhaps viewed as the most risk-based anomaly and serves as a go-to for explaining other anomalies.

Profitability and investment are two factors which are thought to have an impact on future returns of a firm. [Fama & French \(2006\)](#) show that firms with higher operating profitability (scaled by book value of equity) generate higher risk-adjusted returns, while for investment, this relationship is inverse, i.e. high investment level firms generate lower returns. [Titman et al. \(2004\)](#) find a similar pattern, namely that equities with higher investment levels tend to generate lower subsequent returns for up to 5 years past the portfolio formulation. Along with the book-to-market anomaly, they try to reconcile these three patterns with some risk source and show that these patterns can be integrated into the framework of CAPM and do not necessarily violate risk-based asset pricing. In their subsequent work, [Fama & French \(2015\)](#) build on these three 'anomalies' to develop their five-factor model and argue that operating profitability and investment factors might even be used jointly as a proxy for book-to-market factor.

The momentum anomaly was first discussed by [Jegadeesh & Titman \(1993\)](#), with multiple versions of the anomaly, short-term as well as medium to long-term momentum (past 3, 6, 9 and 12 months). According to their results, stocks with better past performance earn higher risk-adjusted returns compared to bad performers. Their findings inspired numerous academic articles to investigate the momentum issue in depth, such

as the application of the momentum phenomenon to mutual funds by [Carhart \(1997\)](#). [Blitz et al. \(2011\)](#) experiment with a residual momentum measure to remove information related to market, size and book-to-market risk factors before investigating the best and worst performers' portfolio returns. Furthermore, [Novy-Marx \(2012\)](#) finds that the momentum effect can be attributed to the intermediate momentum (12 to 7 months) more than the short-term momentum and suggests that intermediate momentum removes some of the most recent fluctuations in prices, thus it is more capable to find stocks with strong recent economic performance. On the other hand, some papers also discuss the reversal of the momentum effect and find evidence that momentum reverses in the long run ([Bondt & Thaler, 1985](#)). As there are numerous other versions of the definition of momentum anomaly variable, it is beyond the scope of this paper to consider all of them, hence only the original [Jegadeesh & Titman \(1993\)](#) previous 12 months momentum is considered for investigating the anomaly's relevance with regards to mispricing.

The anomaly of dividend yields was first documented by [Naranjo et al. \(1998\)](#), but since has been explored in many other papers and in different dimensions as well. [Naranjo et al. \(1998\)](#) find that high dividend payers constitute a portfolio with significantly higher returns compared to low or zero dividend payers and the joint alpha significance test (GRS-test) is significant within an FF3 model explaining the portfolio returns. [Hartzmark & Solomon \(2013\)](#) explore a different aspect of the dividend yield anomaly, where portfolios with impending dividend payments generate significantly higher returns than non-payers or dividend-paying stocks outside their dividend months.

Share issuance based anomalies have been extensively discussed in the literature and many alternative formulations of the issuance anomaly have been developed. For the two types of issuance discussed by [Stambaugh et al. \(2015\)](#) for their mispricing factor, the net stock issues is simply the change in outstanding shares while the composite equity issuance accounts for the market value change of the issued equity as well. [Loughran & Ritter \(1995\)](#) discuss their findings regarding initial public offerings as well as regular equity issuance and find that both groups subsequently underperform firms with no equity issuance for a relatively long period of three years. While the IPO under-performance could be attributed to investor sentiment and overestimation of an IPO stock's future performance resulting in investors driving up the price around the IPO and thus realising lower returns, the same argument would hardly hold for regular equity issuers. [Daniel & Titman \(2006\)](#) show the same effect over the 5-year period of issuance and [Pontiff & Woodgate \(2008\)](#) reinforce these findings when investigating the one-year issuance as well.

[Fama & French \(2008\)](#) investigate this anomaly further and find that while the hedging portfolio on net issuance (long on non-issuers and short on high issuers) has significant returns in the factor model, they aim to produce evidence that this anomaly, along with the others discussed in their paper, can be partially explained by risk sources and argue that the anomaly variable can be a proxy for book-to-market or cash-flow variables, which could further disprove the irrational investor behaviour behind the anomaly. [Chen et al. \(2011\)](#) argue that net stock issues anomaly might be better explained by investment rather than the book-to-market anomaly. On the other hand, [Daniel & Titman \(2006\)](#) present their argument for the book-to-market effect to originate from the intangible part of past returns rather than the accounting-based variables. This means that instead of the book value of the company, determined by the balance sheet variables, it is rather the change in the market capitalization unrelated to the book value which causes the book-to-market effect and they construct the composite equity issuance measure to proxy for the

intangible returns, which they find is in negative relationship with subsequent returns.

The accrual anomaly was first discussed by [Sloan \(1996\)](#), who finds that equities with high accruals subsequently generate lower returns and offers a potential explanation based on earnings. According to the argument, investors might focus extensively on earnings and fail to perceive the distribution of the earnings and its persistence which is relevant for future earnings. The rational expectation is that higher the magnitude of accruals, the harder maintaining high future earnings performance will become. However, investors overestimate the persistence of the accrual component and subsequently judge the high accrual stocks harsher. In addition, [Hirshleifer et al. \(2004\)](#) present the net operating assets anomaly, where they suggest a similar pattern to the accrual anomaly, namely higher net operating assets correspond to lower future returns. Their argument follows the logic that higher net operating assets are a result of crowding out cash flow gains, which might result in investors overestimating the balance sheet value of the company and disregarding prospects on future profitability. [Fairfield et al. \(2003\)](#) connect the two anomalies and show that by dissecting the growth in net operating assets into accruals and long-term net operating assets, both components predict future returns negatively. Hence, while the two anomalies are not necessarily proxies of each other, they are closely related and tell a similar story.

For the distress anomalies, there are two separate methodologies to measure the anomaly variable. One is the O-score ([Ohlson, 1980](#)) discussed in Section 7.1.2. [Dichev \(1998\)](#) presents some evidence that idiosyncratic risk of default measured by either Altman Z-score or O-score for equities do not predict proportionately higher, but in fact lower returns. Consequently, the author argues that default risk is not contained in traditional risk factors, since this would predict higher returns to higher risk associated, but the evidence contradicts this expectation. Alternatively, [Campbell et al. \(2008\)](#) construct their own distress score and find the same results as [Dichev \(1998\)](#) that is the higher distress score corresponds to lower instead of higher subsequent returns.

3 Initial hypotheses

Many of the mentioned anomalies above in Section 2.3 have been shown to cause different asset pricing models to break. According to asset pricing theory, portfolio returns should not have significant excess returns over (or in fact under) the risk factors (no significant alphas) and while different portfolios may react to the risk factor differently and generate significant returns (or losses) unexplained by the risk factor, the joint alpha test of the explained portfolio returns, the GRS-test introduced by [Gibbons et al. \(1989\)](#), should not yield significant results. However, the traditional CAPM model, where equity portfolio returns are explained by market returns, generally fails to explain any of these anomalies. For example, in the case of size and book-to-market anomalies, after showing how models based on market risk fail to explain the anomalies ([Eugene & French, 1992](#)), [Fama & French \(1993\)](#) attempt to reconcile the existence of these anomalies with risk-based asset pricing by constructing risk factors from the size and book-to-market anomalies.

However, [Naranjo et al. \(1998\)](#) show that the dividend yield anomaly cannot be explained by such a three-factor model either. Hence comes the question: is there an underlying risk source for all of the cross-sectional anomalies discovered which one would need to include in a factor model? If not, perhaps some anomalies are simply repackaged version of or proxies for another anomaly. Alternatively, it is possible that these anomalies

are in fact anomalies and cannot be explained with some risk-factor but may be explained with mispricing or investor sentiment, which would have far-reaching implications for the field of asset pricing. [Stambaugh & Yuan \(2017\)](#) attempt to show exactly that while some common risk factor models, such as [Fama & French \(2015\)](#) or [Hou et al. \(2015\)](#), may struggle in explaining many anomalies, a mispricing factor can serve as an efficient augmentation to these models, but without a risk-based explanation behind it.

The initial hypothesis of this paper is that in case an anomaly can be explained with an underlying risk source, then the well-known risk models of FF3 ([Fama & French, 1993](#)) or FF5 ([Fama & French, 2015](#)) should be able to explain the returns on the portfolios created along these anomalies. If anything, the GRS-test of the portfolios formed along the anomalies should prove insignificant. If these models are capable of explaining the returns, the question arises whether substituting the SMB, HML, CMA or RMW factors with the mispricing factors yields the same result. On the other hand, if those models break down in explaining the anomaly returns, perhaps augmenting the models with mispricing factors can help the explanation.

Furthermore, the question of where the anomaly's significance lies can be addressed by investigating the anomaly's significance in separate groups of equities characterised by their mispricing levels. Provided that the main characteristics of equities stay the same across the separate mispricing groups, the same requirement for studying any other cross-sectional anomaly, anomaly portfolios can be established within the mispricing groups to investigate whether their significance stays the same or not. One would expect to see similar relevance if the anomaly has some risk-based explanation, since the underlying risk source should be present and drive returns regardless of the level of mispricing. Alternatively, different levels of significance between using the entire universe of stocks versus only the fair-valued plain of equities to create anomaly portfolios might indicate that the anomaly is more strongly present in over/underpriced stocks than relatively fairly priced stocks, subsequently suggesting that much of the anomaly returns are driven by mispricing instead of a risk factor.

4 Methodology

This section focuses on a broad description of the methodology employed in this paper and specific highlights of it. For a more detailed description of the methodology of obtaining each variable for mispricing measures, data handling, etc. please look for the Appendix under Section 7. The data collected for the analysis in the paper is from the CRSP-Compustat Merged Database (CCM), where the company links between the two different parts are predefined and established. Since the construction of mispricing variables require multiple data sources, the Annual and Quarterly Fundamentals databases are used for accounting and earnings variables, while for stock level data, CRSP Monthly and Daily databases are used. These databases are accessed through the Wharton Research Data Services (WRDS). While some of the anomaly variables are available from 1964 and the [Stambaugh et al. \(2015\)](#) mispricing factor can also be constructed from earlier, the [Bartram & Grinblatt \(2018\)](#) mispricing measure can only be obtained from January 1980. However, the Theil-Sen median version of the BG-factor is only available from February 1980 as January has more than 30 available companies, but less than 100 needed for simulative approach. Besides, one of the anomalies contained in the [Stambaugh et al. \(2015\)](#) measure are only available from later, namely the distress score of

Campbell et al. (2008), which is available from March 1984, hence all tables in Section 5 and Section 7.2 provide the results for this anomaly only from that date. Hence this paper examines the 41-year period spanning between January 1980 and December 2020 for most of the analysis, while few exceptions are applied for the TSBG-factor and the distress anomaly. For portfolio formulation and return analysis, equities must meet four inclusion rules commonly used in asset pricing literature, which are lined out in Section 4.1.

4.1 Mispricing measures

The mispricing measures of Bartram & Grinblatt (2018) and those of Stambaugh & Yuan (2017) are the first to be constructed, and while the cross-sectional portfolio formation requires the exclusion of observations not meeting certain criteria, which will be discussed later, these observations are not excluded until the cross-sectional analysis and portfolio formation to ensure there are no holes in the data. For the Bartram & Grinblatt (2018) variables, a very similar procedure is conducted as to what the authors describe, who obtain 16 balance sheet items, one cash flow statement and 11 income statement items for fitting the market capitalization of firms each month onto these 28 accounting variables. However, this paper uses only 26 of those variables due to non-availability of two variables values, total stockholders equity (TEQQ) and the cash flow item of cash dividends (CDVCY). Hence, there are 15 balance sheet items and 11 income statement items used for estimating the value of the stock each month by the regression described in Equation (1). While the authors consider the last available quarter's information, the procedure of this paper looks independently for all of the last available accounting variables. The availability requirement contains two conditions: the variable must have a non-missing value and there is a minimum and maximum release date requirement. The minimum release date requirement is described in more details in Section 7.1.1, but the general motivation is to use the most up-to-date information while avoiding the use of non-public information. For the maximum requirement, an accounting variable is set for missing, if the necessary quarterly data (one point-in-time for balance sheet and four for income statement variables) cannot be found publicly available in the last 2 years.

Once the 26 accounting variables are obtained, the estimation of fair values for the universe of stocks available for each month follows. This cross-sectional regression estimation for any month requires at least 30 firms in the sample and has no constant to place part of the valuation not stemming from accounting variables in the residual term measuring misvaluation. An inclusion rule is set up from 4 different requirements, any firm-month observation must meet all 4 to be included in the cross-sectional analysis of portfolio formation, factor production and explanation of returns. All observations must have an ordinary CRSP share code (SHRCD of 10 or 11), must be traded on the 3 major US stock exchanges (EXCHCD of 1, 2 or 3), must have a price not lower than 5\$ and must be a non-financial firm (SIC not between 6000 and 6999) to avoid potential biases in portfolio returns. If a firm-month observation meets all four of these requirements, it is included in the monthly estimation of fair valuation. The 26 independent variables are ought to provide the peer-to-peer fair value estimate for firm i and month t and the residual term provides the difference of the market cap and the estimated fair value, i.e. the mispricing component of a company's stock price. The regression equation for any

month t and company i is formed as:

$$\begin{aligned}
MarketCap_{i,t} = & \beta_{1,t} * SALEQ_{i,t} + \beta_{2,t} * IBQ_{i,t} + \beta_{3,t} * NIQ_{i,t} + \beta_{4,t} * XIDOQ_{i,t} \\
& + \beta_{5,t} * NOPIQ_{i,t} + \beta_{6,t} * DOQ_{i,t} + \beta_{7,t} * IBADJQ_{i,t} \\
& + \beta_{8,t} * IBCOMQ_{i,t} + \beta_{9,t} * PIQ_{i,t} + \beta_{10,t} * TXTQ_{i,t} \\
& + \beta_{11,t} * DVPQ_{i,t} + \beta_{12,t} * ATQ_{i,t} + \beta_{13,t} * LCOQ_{i,t} \\
& + \beta_{14,t} * SEQQ_{i,t} + \beta_{15,t} * ICAPTQ_{i,t} + \beta_{16,t} * PSTKRQ_{i,t} \\
& + \beta_{17,t} * PPENTQ_{i,t} + \beta_{18,t} * CEQQ_{i,t} + \beta_{19,t} * PSTKQ_{i,t} \\
& + \beta_{20,t} * DLTTQ_{i,t} + \beta_{21,t} * AOQ_{i,t} + \beta_{22,t} * LTQ_{i,t} + \beta_{23,t} * LOQ_{i,t} \\
& + \beta_{24,t} * CHEQ_{i,t} + \beta_{25,t} * ACOQ_{i,t} + \beta_{26,t} * APQ_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{1}$$

The mispricing signal itself, which provides the basis of the ranking of a stock in each month, is then constructed from these fitted values. The methodology draws the inspiration from [Bartram & Grinblatt \(2018\)](#), however reverses the sign so that the undervalued-overvalued lineup is consistent with the other mispricing measure of [Stambaugh & Yuan \(2017\)](#).

The alternative measure used for establishing mispricing measures for companies and subsequently a factor is the [Stambaugh & Yuan \(2017\)](#) methodology. For this analysis, 11 anomaly variables and rankings are established based on anomalies most commonly associated with mispricing. These rankings are then averaged out for every firm-month observation to obtain the mispricing signal of a company relative to its peers. These 11 anomalies are: net stock issues, composite equity issues, accruals, net operating assets, investment-to-assets, distress, o-score, momentum, gross profitability premium, return on assets. While most of these anomalies behave in a way that higher the ranking on the anomaly variable, the more overvalued and lower subsequent returns are expected, the last 3 anomaly rankings of momentum, gross profitability and return on assets are reversed to make the averaging-out more consistent ([Stambaugh et al., 2015](#)). Since these anomaly variables require multiple sub-variables from across different databases, the detailed description of constructing these variables can be found in Section 7.1.2. For annual accounting items, the last year’s reported data is used, provided that the variable is not missing and the year ended 4 months before the portfolio formation month (5 months before the holding period). For quarterly items, the same methodology is followed as for the [Bartram & Grinblatt \(2018\)](#) variables, namely using the final release date, or the one-month lagged information from the earnings report date, or if both are unavailable, then the release date of accounting information is set to 6 months from the end date of the fiscal period. For stock-level and market-level data, the same methodology is followed as the one described by [Stambaugh & Yuan \(2017\)](#).

4.2 Construction of anomaly dependent variables

This subsection describes the methodology of obtaining some of the cross-sectional anomalies investigated in the paper. However, some anomaly variables will not be discussed here as the methodology regarding those variables is described in Section 7.1.2. Namely, the net stock issues (Equation 9), composite equity issues (Equation 10), accruals (Equation 11), net operating assets (Equation 13), investment to assets (Equation 17), distress (Equation 18), O-score (Equation 22) and return on assets (Equation 25) anomaly vari-

ables can be found along with the other Stambaugh-Yuan anomaly descriptions in Section 7.1.2. While the momentum anomaly is included below to emphasise it along with the anomalies used for the five-factor construction, the asset growth and gross profitability anomalies from the Stambaugh-Yuan collection are omitted due to their similar nature to the five-factor model anomalies of operating profitability and investment growth.

The size anomaly is measured by market capitalization of firms for the portfolio formation. This market capitalization is simply the portfolio formation month $t - 1$ closing price times the outstanding shares, both data-points obtained from the CRSP database for any firm-month observation. The measure for book-to-market value uses this same market capitalization measure for firm size. The book value for anomaly and factor creation is defined as the total assets minus the total liabilities of a firm to calculate total book equity. The release date requirement is similar to the that defined by [Stambaugh & Yuan \(2017\)](#) instead of the more restricting 6 month period required by [Fama & French \(2015\)](#). This methodology is slightly different from that of [Fama & French \(2015\)](#), who correct this book value calculation with a few small items as well, yet these corrections should not create substantial differences in book value calculation.

The operating profitability measure construction mimics the one by [Fama & French \(2015\)](#), except that the release date information requirement is the slightly more forgiving version of [Stambaugh & Yuan \(2017\)](#). The operating profits are calculated as revenues (Compustat item REVT) minus cost of goods sold (COGS), interest expenses (XINT), general and selling and administrative expenses (XGSA). This profit measure is then scaled by the book value of equity. The investment growth measure is quite straightforward to construct, [Fama & French \(2015\)](#) defines it as the change between the last year's total assets and the previous year's before that ($t - 1$ and $t - 2$ respectively), scaled by the assets of year $t - 2$.

The momentum anomaly variable for constructing portfolio returns on the dependent side matches the methodology of the momentum variable for the mispricing measure of [Stambaugh & Yuan \(2017\)](#), that is for portfolio formation month $t - 1$, the cumulative returns across $t - 12$ to $t - 2$, also described by [Jegadeesh & Titman \(1993\)](#), one of the first papers on the momentum anomaly.

Following the first paper on dividend yield anomaly, the methodology of constructing the anomaly variable is that of the one defined by [Naranjo et al. \(1998\)](#). That is, the dividend yield for month t is calculated by the following:

$$DY_t = \frac{4D}{P_{t-1}} \quad (2)$$

where D is the most recent announced dividend in the past 12 months. The inclusion rules must be met by any firm-month observation to qualify for the dividend portfolio formation.

4.3 Factor formulation

The factors in question are the factors of the five-factor model ([Fama & French, 2015](#)), the mispricing factors of [Stambaugh & Yuan \(2017\)](#) and the mispricing factor constructed from the fair-value estimation of [Bartram & Grinblatt \(2018\)](#). These factors are constructed on double sorted portfolios, averaging out the value-weighted returns of portfolios to get the factor returns.

For the size and the book-to-market anomalies, the entire universe of stocks eligible

for the portfolio inclusions based on the four inclusion rules described in Section 4.1 are sorted into 2x3 portfolios, following Fama & French (1993), to construct the size and book-to-market anomalies. Each month, stocks are broken up into two halves to identify companies with market capitalization lower and higher than the cross-sectional median. For the book-to-market sorts, the breakpoints of 30th and 70th percentiles are used as breakpoints to construct BM1 (value), BM2 (neutral) and BM3 (growth) portfolios. For the other two factors of the five-factor model, OP and INV, the same approach is used for the 3 portfolios in each size median group, that is, the double-sort is based on 2x3 on size and OP or INV respectively. For the operating profitability, Fama & French (2015) describes the three portfolios as OP1 (low profit or weak), OP2 (neutral) and OP3 (high profit or robust), while for the investment portfolios are named as INV1 (low or conservative), INV2 (neutral) and INV3 (high or aggressive).

Hence, the factors of the value factor (HML), profitability (RMW) and investment (CMA) are constructed as described in Equation (3), Equation (4) and Equation (5) respectively. While the factors of BM, OP and INV are constructed from one double-sort, the size sort is the average of the 3 calculated SMB-factors on the 3 sorts in the five-factor model as Equation (6) shows.

$$HML_t = (SmallValue_t + BigValue_t)/2 - (SmallGrowth_t + BigGrowth_t)/2 \quad (3)$$

$$RMW_t = (SmallRobust_t + BigRobust_t)/2 - (SmallWeak_t + BigWeak_t)/2 \quad (4)$$

$$CMA_t = (SmallConservative_t + BigConservative_t)/2 - (SmallAggressive_t + BigAggressive_t)/2 \quad (5)$$

The size factor, also called as small-minus-big (SMB) is constructed as shown in Equation (6).

$$SMB_t = (SMB_t^{BM} + SMB_t^{OP} + SMB_t^{INV})/3 \quad (6)$$

$$SMB_t^{BM} = (SmallValue_t + SmallNeutral_t + SmallGrowth_t)/3 - (BigValue_t + BigNeutral_t + BigGrowth_t)/3 \quad (6a)$$

$$SMB_t^{OP} = (SmallRobust_t + SmallNeutral_t + SmallWeak_t)/3 - (BigRobust_t + BigNeutral_t + BigWeak_t)/3 \quad (6b)$$

$$SMB_t^{INV} = (SmallConservative_t + SmallNeutral_t + SmallAggressive_t)/3 - (BigConservative_t + BigNeutral_t + BigAggressive_t)/3 \quad (6c)$$

For the mispricing factors, the factor construction is quite similar to the technique of Fama & French (1993), that is the stocks are double-sorted into 2x3 portfolios based on size and the mispricing variable. However, instead of using the 30th and 70th percentile breakpoints, the 20th and 80th percentile breakpoints are utilized for mispricing, since Stambaugh & Yuan (2017) argue that the most substantial influence of mispricing lies in the extreme legs of the spectrum, hence most likely mispricing is best represented by the undervalued lowest and overvalued highest quantiles. Hence the construction of the

SY-mispricing factor is described in Equation (7). For the Bartram & Grinblatt (2018) mispricing factor, the same methodology is followed as the SY-mispricing factor, and this construction of the BG-mispricing factor is described in Equation (8).

$$SY_t = (SmallUndervaluedSY_t + BigUndervaluedSY_t)/2 - (SmallOvervaluedSY_t + BigOvervaluedSY_t)/2 \quad (7)$$

$$BG_t = (SmallUndervaluedBG_t + BigUndervaluedBG_t)/2 - (SmallOvervaluedBG_t + BigOvervaluedBG_t)/2 \quad (8)$$

5 Results

5.1 Anomalies with traditional factor models

In order to investigate the explanatory power of mispricing on the selected cross-sectional anomalies, these anomalies can be investigated by estimating their returns with some well-known factor models, such as the CAPM, FF3 or FF5 models. The factor models are used to estimate the α -s on the decile value-weighted portfolio returns to determine whether the particular portfolio has a significant return over the risk factors of the model. According to asset pricing theory, if the factor model is an adequate representation of risk factors driving prices, the α -s on the portfolios should not be significantly different. An even better test of the performance of the factor model to explain a particular anomaly is the application of the GRS-test. The 14 anomalies used for testing the mispricing factor performances are all estimated with the CAPM, FF3 and FF5 to evaluate the α -s and the GRS-test results.

5.1.1 Anomalies explained by CAPM

Table 8 shows the results on the explanatory power of CAPM on the 14 anomalies. The general pattern shows that for the given parameters (described at Table 8), the CAPM model is generally unable to explain the excess returns on the anomaly portfolios. The last column contains the GRS-test results, which for every particular anomaly out of the 14 considered anomalies yields a significant rejection of the null hypothesis. This means that CAPM is virtually incapable of pricing the excess returns of the 10 decile portfolios, because the portfolios together have significant α -s over the market risk factor.

Besides this, an important observation can be drawn by looking at the α -s of the 10 decile portfolios from D1 to D10, namely that with barely any exceptions, all portfolio value-weighted returns for all anomalies have significant positive returns over the market risk. This could indicate that indeed there exist some sources of risk undefined by the Capital Asset Pricing Model, which could drive the risk premium on these portfolios higher, resulting in a consistent underestimation of returns by CAPM.

Furthermore, one needs to look at the hedging portfolios of D1-D10 in Table 1 in order to determine the direction in which the anomaly generates excess returns and whether this is consistent with previous literature presented in Section 2.3. Out of the 14 anomalies, only 5 generate non-significant α -s on the hedging portfolio, while 9 other anomalies do. However, even for these 5 anomalies, the CAPM model would break down, hence the anomalies' dubious existence does not acquit the model but rather raises questions whether the anomalies generate significant trading opportunities which could be exploited by rational traders.

Table 1: Alpha coefficients for anomaly hedge portfolios for the entire period 1980-2020

	Base models			Augmented SY			Augmented BG			Augmented Theil-Sen median BG		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
Size	0.0194*** (9.84)	0.0076*** (5.96)	0.0073*** (5.67)	0.0221*** (11.89)	0.0079*** (5.90)	0.0081*** (6.06)	0.0194*** (9.91)	0.0075*** (5.90)	0.0072*** (5.58)	0.0192*** (9.79)	0.0074*** (5.74)	0.0070*** (5.32)
BM	-0.0068** (-2.67)	0.0028 (1.62)	0.0024 (1.36)	-0.0097*** (-3.91)	-0.0010 (-0.59)	-0.0015 (-0.88)	-0.0071*** (-3.44)	0.0023 (1.37)	0.0014 (0.87)	-0.0078*** (-4.09)	0.0013 (0.78)	-0.0003 (-0.17)
OP	0.0034 (1.61)	-0.0029 (-1.53)	0.0014 (1.08)	0.0072*** (3.87)	0.0023 (1.22)	0.0016 (1.18)	0.0033 (1.66)	-0.0032 (-1.72)	0.0015 (1.10)	0.0029 (1.49)	-0.0043* (-2.32)	0.0012 (0.91)
INV	-0.0068** (-2.67)	0.0028 (1.62)	0.0024 (1.36)	-0.0097*** (-3.91)	-0.0010 (-0.59)	-0.0015 (-0.88)	-0.0071*** (-3.44)	0.0023 (1.37)	0.0014 (0.87)	-0.0078*** (-4.09)	0.0013 (0.78)	-0.0003 (-0.17)
DP	0.0020 (0.80)	0.0031 (1.18)	0.0018 (0.69)	0.0003 (0.10)	-0.0005 (-0.16)	-0.0006 (-0.21)	0.0020 (0.79)	0.0030 (1.15)	0.0015 (0.58)	0.0018 (0.73)	0.0025 (0.96)	0.0003 (0.13)
MOM	-0.0092* (-2.58)	-0.0159*** (-5.02)	-0.0140*** (-4.44)	-0.0034 (-1.04)	-0.0038 (-1.31)	-0.0031 (-1.12)	-0.0089** (-3.09)	-0.0146*** (-4.99)	-0.0120*** (-4.15)	-0.0078** (-2.86)	-0.0121*** (-4.24)	-0.0081** (-2.94)
NETSTO	0.0032* (2.32)	0.0047** (3.21)	0.0031* (2.20)	0.0015 (1.14)	0.0016 (1.10)	0.0019 (1.27)	0.0033* (2.41)	0.0049*** (3.45)	0.0035* (2.48)	0.0034* (2.48)	0.0054*** (3.74)	0.0039** (2.71)
COMPEQ	-0.0007 (-0.38)	0.0018 (0.99)	0.0021 (1.13)	-0.0017 (-0.95)	0.0006 (0.31)	0.0004 (0.21)	-0.0007 (-0.38)	0.0020 (1.08)	0.0024 (1.31)	-0.0006 (-0.36)	0.0023 (1.27)	0.0031 (1.69)
ACCR	0.0010 (0.53)	0.0044* (2.34)	0.0036 (1.93)	-0.0007 (-0.40)	0.0023 (1.16)	0.0028 (1.43)	0.0010 (0.54)	0.0045* (2.35)	0.0038* (2.05)	0.0010 (0.52)	0.0047* (2.47)	0.0044* (2.35)
NETOPA	0.0072*** (4.11)	0.0092*** (5.23)	0.0097*** (5.54)	0.0064*** (3.62)	0.0077*** (4.17)	0.0076*** (4.23)	0.0072*** (4.22)	0.0091*** (5.16)	0.0097*** (5.54)	0.0069*** (4.10)	0.0089*** (5.03)	0.0098*** (5.53)
INVTOA	0.0030* (2.01)	0.0018 (1.15)	0.0008 (0.55)	0.0020 (1.36)	-0.0009 (-0.54)	-0.0002 (-0.18)	0.0030* (2.01)	0.0018 (1.12)	0.0010 (0.71)	0.0030* (2.01)	0.0020 (1.28)	0.0017 (1.25)
DISTRESS	-0.0035 (-1.23)	0.0020 (0.70)	-0.0006 (-0.21)	-0.0081*** (-3.32)	-0.0066* (-2.49)	-0.0070** (-2.65)	-0.0034 (-1.20)	0.0020 (0.71)	-0.0008 (-0.30)	-0.0034 (-1.21)	0.0014 (0.49)	-0.0025 (-0.90)
OSCORE	-0.0127*** (-3.84)	-0.0015 (-0.65)	-0.0043* (-2.20)	-0.0178*** (-5.77)	-0.0059* (-2.46)	-0.0060** (-2.95)	-0.0125*** (-4.62)	-0.0006 (-0.26)	-0.0034 (-1.81)	-0.0115*** (-4.39)	0.0016 (0.81)	-0.0014 (-0.76)
RETONA	-0.0052* (-2.05)	0.0031 (1.34)	-0.0004 (-0.19)	-0.0110*** (-5.28)	-0.0055** (-2.61)	-0.0059*** (-3.47)	-0.0051* (-2.12)	0.0035 (1.55)	-0.0003 (-0.17)	-0.0048* (-1.98)	0.0043 (1.91)	-0.0005 (-0.25)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

For the size anomaly, the anomaly shows a really strong hedging portfolio return with average 1.94% monthly return over the estimated return by CAPM, with the D1 (small caps) generating higher returns than the D10 (large caps). The ten portfolios from D1 to D10 also suggest a general decreasing trend in α , in line with the prediction of the literature. A similar goes for the book-to-market anomaly (BM) as well, with the high BM portfolio (D10) having an average 68 basis point return over the low BM portfolio (D1). The pattern of α -s is also increasing, which corresponds to previous literature with the notable exception of the D1 portfolio returns, which is much higher than those of D2 or D3.

On the other hand, the operating profitability (OP) and dividend yield (DP) anomalies show no sign of significant returns on the hedging portfolios and no clear trend in the estimated excess returns over market risk along the deciles. The investment anomaly (INV) shows signs of relatively smaller but still significant hedging portfolio excess returns with low investment (D1) portfolio earning 37 basis points on average over the high investment portfolio (D10).

The momentum anomaly (MOM) shows a rather strong presence, where the strongest performers' portfolio (D10) earns an average 92 basis points monthly over the lowest performers (D1). However, the trend again looks interesting with higher returns on the extremes (D1 or D10) and a saddle between them with lower returns. Furthermore, low net stock issuers (NETSTO) have a small but significant at 10% excess return over the large issuers, earning on average 32 basis points, which is consistent with the literature. However, the α is quite volatile across the deciles which might be attributed to the minor data issues of cutting up the portfolios.

On the other hand, the composite equity issuers (COMPEQ) and the accruals (ACCR) anomalies show no sign of significant excess return difference between D1 and D10. Both anomalies show a similar pattern to the momentum α -s, namely that excess returns on the extreme portfolios are high and lower in between, however, the two ends of the extreme generate around the same excess returns. In case of the distress anomaly, it is even more

puzzling, as the higher distress score portfolios seem to generate higher excess returns (D10 with an average 1.12% monthly) contradicting the literature, with less distressed companies earning an estimated 35 basis points below this, however, due to the large variance in the data, this difference is not significant.

Both net operating assets (NETOPA) and investment to assets (INVTOA) have decreasing pattern in α -s from D1 to D10 and a significant return on the hedging portfolio as predicted by previous literature. However, the O-score measure of default probability presents an anomaly in the complete opposite way as the literature predicts it. Distressed companies earn significantly over non-distressed companies, with an average hedging portfolio α of 1.27% of D10 over D1. Furthermore, since the ranking on the return on assets (RETONA) anomaly is reversed, D1 represents the highest return on assets and D10 the lowest. Hence, this finding also contradicts the prediction of the literature, where a portfolio of firms generating lower return on assets (D10) subsequently achieve higher returns on the stock market compared to the highest return-to-assets ratio portfolio (D1). Nevertheless, interestingly the similar pattern emerges, where the extremes have higher α -s compared to the portfolios in the middle of the ranking.

5.1.2 Anomalies explained by FF3

In comparison with the portfolio returns explained by CAPM in Section 5.1.1, the FF3 model seems to reduce the GRS t-statistics in most cases (although quite noticeably it increases for the size anomaly) but not enough to render the tests statistically insignificant, hence the performance of the FF3 model to explain the anomaly portfolio returns seems unconvincing. However, out of the 14 anomalies, only 5 present significant hedging portfolio returns compared to the 9 anomalies in the case of CAPM (Table 1). Most interestingly, while the FF3 reduces the magnitude of the size effect, it deepens the rift between the extreme portfolios in the case of the momentum, net stock issues, net operating assets and creates a significant difference for accruals. Thus, while FF3 brings a more significant model improvement relative to CAPM than the FF5 brings relative to FF3, this model is not infallible either and falls short on pricing the anomalies correctly for the entire period of 1980-2020.

By introducing the size and book-to-market factors, the size anomaly's magnitude is visibly reduced as many portfolio α -s from D1 to D9 are practically halved, but this does not remove the significance of the hedging portfolio's excess returns over the risk factors and small companies still over-perform large companies by an average of 76 basis points monthly. On the other hand, the book-to-market and investment anomalies are reduced insignificant based on the hedging portfolio and the operating profitability and dividend yield anomalies stay irrelevant by the same measure.

A puzzling comparison to the CAPM model, however, is that the FF3 model increases the magnitude of the momentum and the net stock issues anomalies as well. While these anomalies bear significant hedging portfolio excess returns in the CAPM framework as presented in Section 5.1.1, the FF3 model seems to exacerbate the difference between the high momentum and low issuers and the low momentum and large issuers respectively. What is even more puzzling is the incapability of the FF3 model to explain the hedge α on the accruals anomaly whereas CAPM can effectively render this α insignificant, indicating that accruals would present a trading opportunity in an FF3 framework but not so much in a CAPM framework.

Furthermore, the spread between D1 and D10 estimated α -s for net operating assets

is also increased from the CAPM to FF3 by a 20 basis points. On the other hand, FF3 is capable of explaining the spreads for the investments-to-assets, O-score and return on assets anomalies, while holding the α -s on the spreads for COMPEQ and DISTRESS anomalies insignificant.

5.1.3 Anomalies explained by FF5

Compared to the results presented in Section 5.1.2, the results in this section are estimated with the extended Fama-French model, supplementing the SMB and HML factors with the CMA and RMW factors (investment and operating profitability factors respectively). First and foremost, while the FF3 model was capable of rendering a few individual portfolio (D1 to D10 through all anomalies) α -s insignificant, the FF5 model explains even fewer individual α -s, albeit still more than the CAPM. Nevertheless, the GRS-tests for all anomalies still yield significant rejection of the null hypotheses, hence this model is no more capable of explaining the returns on each of the anomalies than the previous factor models.

For the hedging portfolios, a similar performance can be shown to FF3, namely that 5 out of the 14 anomalies have significant α -s on the hedging portfolios. While the size, momentum, net stock issues and net operating assets remain significant hedges, the accruals anomaly barely disappears in terms of significance while the O-score barely raises a significant difference between the D1 and D10 portfolios, however still in the opposite direction as to how the literature predicts it, namely distressed companies generate higher returns than financially stable companies. At the same time, all the other anomalies, which were predicted to present no significant hedging portfolio excess returns by the three-factor model are also rendered insignificant by the five-factor model.

5.2 Augmenting factor models with mispricing factors

After having seen how the CAPM, FF3 and FF5 models fall short on providing an adequate explanation to the set of 14 anomalies, the main research question comes into focus - can mispricing factors augment these models so that the anomaly hedge α -s or even the GRS-tests are rendered insignificant? Can such factors enhance the effectiveness of the traditional models to explain the anomalous patterns, further cementing the notion that these anomalies cannot be effectively explained by risk but rather investor sentiment? Table 1 provides an overview on the hedge portfolio α -s in the base models as shown before, and their augmented versions with the [Stambaugh & Yuan \(2017\)](#) mispricing factor, the mispricing factor created from the signal described by [Bartram & Grinblatt \(2018\)](#) and its Theil-Sen median estimate obtained from the simulative approach.

5.2.1 Augmenting with the SY-factor

Perhaps the biggest improvement in the hedge α -s is the result of model augmentation with the SY mispricing factor. The mispricing factor offers little to no help in explaining Size, BM or INV anomalies, and even obstructs CAPM from rendering the OP hedge α -s insignificant. Nevertheless, the augmented FF3 and FF5 effectively explains all of these anomalies except Size, indicating that the Fama-French risk factors are more important than the mispricing factor in explaining these patterns. The dividend yield proves completely insignificant as before, and in fact not only the SY-augmentation, but the BG and TSBG extensions estimate an insignificant risk-adjusted return. This leaves only a few

options for the dividend yield anomaly, namely that the anomaly’s significance is either time-sensitive (portfolio formulation as well as estimation period), lies between payers and non-payers (Hartzmark & Solomon (2013) suggests a combination of these two), or that the anomaly is in fact not significant consistently.

The rest of the 14 anomalies are 9 anomalies that are strictly part of the SY-factor’s construction mechanism. Hence, the explanatory power of SY-factor on these anomalies should be expected to increase, just as the explanatory power of the SMB, HML, CMA or RMW factors are relatively strong for the size, book-to-market, profitability or investment patterns. However, the SY-factor is constructed from 11 different anomaly rankings as described in Section 7.1.2, and thus except for the distress and return-on-assets anomalies (correlation of approximately 0.6), none of the anomalies have a higher absolute correlation than 0.5 with the factor. This correlation in the case of SMB with the size hedge is 0.77, 0.69 for HML and BM-hedge, 0.76 for CMA and INV-hedge and -0.8 for OP-hedge (D1-D10) and RMW. With this in mind, the momentum and net stock issuance anomaly hedges, while consistently unexplained by the three base models, are rendered insignificant with the help of the SY mispricing factor.

On the other hand, while the α -s are reduced in magnitude for the net operating assets compared to the base models, their significance is not affected. Even more concerning is the SY factor’s performance in the case of the distress, O-score and return-on-assets anomalies. While CAPM is generally of poor performance in explaining the hedges, FF3 can effectively price all three of these anomalies’ hedge portfolios. On the other hand, the inclusion of the SY-factor seems to upset this balance and significantly reduces the α -s in magnitude, thus creating significant differences in pricing the D1 and D10 portfolios of these three anomalies. If one looks into the factor loadings of the SY-factor for the various anomalies, a common pattern emerges among the three anomalies where the SY-factor deepens the α ’s magnitude and significance. This pattern shows, that the factor loadings of the mispricing factor are significantly positive and high in magnitude compared to the rest of the anomalies. A strong positive coefficient implies a reduction in α when the mispricing factor’s value is positive, i.e. there is a decreasing level of relative mispricing, which intuitively makes sense as the previously higher α -s need to be adjusted for lower relative mispricing levels. However, the hedge α -s of these anomalies were considerably well explained by the base models, specifically FF3 and FF5, and hence an inclusion of the SY-factor and its strongly positive coefficients now estimate strongly negative α -s on the hedge portfolios. A negative alpha on the hedges of these three anomalies contradict the findings of the literature, where these α -s are predicted significantly positive (in the case of the RETONA, a positive alpha is expected due to the reversal of the ordering, i.e. the lowest decile is the highest earner).

5.2.2 Augmenting with the BG-factor and its alternative

Table 1 provides the estimation of hedge α -s by the augmented models with BG-factor as well as its simulative Theil-Sen median version (TSBG-factor). In general, these mispricing factors, albeit they are supposed to serve a similar function to the SY-factor, perform worse and their inclusion in the traditional factor models does little to explain the anomaly hedge returns. In general, while the inclusion of these factors may reduce the magnitude of the α -s in some cases as compared to the ordinary CAPM, FF3 or FF5 models, this rarely corresponds to significance level reduction. In fact if anything, the inclusion of an extra factor reduces the variation enough to increase the significance

level in some cases, such as the BM, INV, MOM, NETSTO, and ACCR anomalies. Most notably, while the inclusion of the BG-factor, but especially the TSBG-factor reduces the magnitude of the α -s on the momentum anomaly, this is not sufficient for rendering the hedge α -s insignificant.

However, this does not mean that the factor serves as a poor predictor for portfolio returns. Table 11 through Table 24 in Section 7.2 presents the factor loadings on the hedge portfolios. Especially when augmenting CAPM, the BG-mispricing factor often serves as an important predictor of excess returns. While the TSBG-factor results are not laid out in detail in these tables, their loadings' significance is generally even higher, improving factor significance compared to BG-factor in the case of investment, composite equity issuance, accruals, investment-to-assets and even the distress anomaly. Nevertheless, the BG-factor and its variant do not seem to improve the base models by much and strikingly, even increase the significance of the unexplained part of hedging returns, indicating that their performance on the entire period of 1980-2020 does not justify their inclusion.

When looking at the factors' loadings across Table 11 through Table 24, one might also notice that while in some cases, the SY and BG factors serve a similar role (such as in the case of profitability in Table 13, net stock issuance in Table 17 or O-score in Table 23), there are some cases of striking difference in loadings for the same anomaly. The two most notable cases are the book-to-market and the momentum anomalies. For the book-to-market anomaly, while the SY-factor had significantly positive loadings on the hedge returns, with a rather monotone trend with the highest loading on D1 and lowest on D10, the BG-factor reverses this completely, with significantly negative loadings on the hedges and a monotone trend of lowest loading on D1 and highest on D10. At the same time, their ability to predict hedge α -s (as well as the D1 to D10 α -s) are quite similar. This implies that the absolute correlation between the two factors are low, as this is the case with the SY-factor sharing a 0.09 correlation with the BG-factor (same correlation applies to TSBG as well). The importance of this lies in the fact that both mispricing factors are meant to represent the same information with different approaches, that is the level of relative mispricing in the market. In the case of the momentum anomaly, the reverse of this applies, i.e. the SY-factor has significantly negative loadings on hedges and the BG-factor has significantly positive loadings. Particularly puzzling is the fact that both anomalies meant to point in one direction, that is in both cases, literature predicts the D10 portfolio to have significant returns over the D1 (high book-to-market ratio companies outperform those with low ratios and high momentum companies outperform low momentum companies). Eventually, the inclusion of mispricing factors offers no help in the reduction of the GRS test significance compared to the base models, that is for all anomalies for the entire period, these models do not adequately explain the 10 decile portfolio returns.

5.3 Decade-wise analysis of anomalies

As the discussion in Section 5.1 and in Section 5.2 presented, the performance of the basic factor models and their augmented versions in explaining the anomaly returns are rather mixed. The models in general cannot price the returns properly for the entire period of 1980-2020 and the hedging portfolios often have significant returns over the factors included in the models. These significant α -s are seldom reduced to insignificant α -s by the help of mispricing factors, but more often their significance is left untouched, indicating that these anomalies cannot be explained by the mispricing factors either. Another puzzle

Table 2: Alpha coefficients for anomaly hedge portfolios with basic models

	1980-1989			1990-1999			2000-2009			2010-2020		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
Size	0.0180*** (4.65)	0.0096*** (4.81)	0.0100*** (4.49)	0.0144*** (3.67)	0.0045* (2.13)	0.0033 (1.55)	0.0254*** (6.56)	0.0055 (1.81)	0.0055 (1.81)	0.0191*** (4.70)	0.0109*** (3.87)	0.0105*** (3.84)
BM	-0.0039 (-0.95)	0.0064*** (2.80)	0.0060* (2.27)	-0.0002 (-0.05)	0.0063* (2.61)	0.0066** (2.70)	-0.0260*** (-4.16)	0.0001 (0.01)	0.0002 (0.04)	0.0009 (0.22)	0.0042 (1.37)	0.0046 (1.49)
OP	-0.0013 (-0.35)	-0.0095** (-2.87)	-0.0009 (-0.34)	0.0089 (1.79)	0.0031 (0.71)	0.0062* (2.11)	0.0054 (1.04)	-0.0027 (-0.65)	-0.0031 (-1.10)	0.0033 (1.39)	0.0008 (0.34)	0.0001 (0.06)
INV	0.0074* (2.59)	0.0042 (1.47)	-0.0018 (-0.68)	-0.0011 (-0.31)	0.0002 (0.05)	-0.0056* (-2.22)	0.0073 (1.65)	0.0010 (0.19)	0.0018 (0.58)	-0.0003 (-0.10)	0.0002 (0.06)	-0.0012 (-0.47)
DP	0.0001 (0.04)	0.0028 (0.87)	0.0047 (1.23)	-0.0057 (-1.42)	-0.0048 (-1.14)	-0.0048 (-1.20)	-0.0058 (-1.27)	-0.0044 (-0.80)	-0.0041 (-0.79)	0.0174** (2.63)	0.0182** (2.65)	0.0185** (2.69)
MOM	-0.0063 (-1.18)	-0.0177*** (-3.98)	-0.0105* (-2.14)	-0.0135* (-1.98)	-0.0187*** (-3.86)	-0.0165** (-3.36)	0.0010 (0.10)	-0.0146 (-1.60)	-0.0151 (-1.80)	-0.0099 (-1.73)	-0.0127* (-2.26)	-0.0123* (-2.23)
NETSTO	0.0051* (2.19)	0.0036 (1.48)	-0.0028 (-1.08)	0.0011 (0.35)	0.0043 (1.45)	0.0042 (1.40)	0.0039 (1.22)	0.0022 (0.56)	0.0024 (0.66)	0.0015 (0.58)	0.0026 (1.23)	0.0036 (1.48)
COMPEQ	0.0040 (1.29)	0.0075* (2.39)	-0.0002 (-0.06)	-0.0004 (-0.13)	0.0031 (1.05)	0.0031 (1.06)	-0.0024 (-0.57)	-0.0010 (-0.20)	-0.0010 (-0.21)	-0.0008 (-0.22)	0.0014 (0.39)	0.0016 (0.46)
ACCR	0.0044 (1.38)	0.0079* (2.58)	0.0056 (1.64)	0.0079 (1.96)	0.0124** (3.18)	0.0099* (2.58)	-0.0039 (-0.96)	-0.0009 (-0.17)	-0.0005 (-0.11)	-0.0029 (-0.84)	-0.0013 (-0.38)	-0.0013 (-0.38)
NETOPA	0.0038 (1.51)	0.0049 (1.88)	0.0046 (1.53)	0.0082 (1.91)	0.0132*** (3.44)	0.0139*** (3.53)	0.0066 (1.56)	0.0117** (2.73)	0.0118** (2.82)	0.0090** (3.18)	0.0080** (2.84)	0.0083** (2.98)
INVTOA	0.0072** (2.88)	0.0039 (1.55)	0.0015 (0.60)	0.0035 (1.12)	0.0052 (1.63)	0.0015 (0.53)	0.0022 (0.66)	-0.0005 (-0.12)	-0.0002 (-0.06)	-0.0009 (-0.31)	-0.0011 (-0.37)	-0.0022 (-0.82)
DISTRESS	-0.0024 (-0.59)	-0.0002 (-0.04)	0.0003 (0.07)	-0.0061 (-1.82)	-0.0072* (-2.09)	-0.0073* (-2.07)	-0.0042 (-0.61)	0.0028 (0.35)	0.0035 (0.50)	-0.0078 (-1.45)	-0.0004 (-0.07)	0.0001 (0.02)
OSCORE	-0.0044 (-1.15)	0.0025 (1.10)	-0.0019 (-0.86)	-0.0163* (-2.34)	-0.0057 (-1.29)	-0.0072 (-1.83)	-0.0172 (-1.84)	-0.0081 (-1.37)	-0.0084 (-1.65)	-0.0114* (-2.07)	-0.0016 (-0.35)	-0.0007 (-0.17)
RETONA	0.0017 (0.48)	0.0115*** (3.73)	0.0071* (2.44)	-0.0047 (-1.03)	0.0010 (0.24)	0.0010 (0.29)	-0.0070 (-1.04)	0.0011 (0.18)	0.0012 (0.25)	-0.0138** (-2.97)	-0.0055 (-1.46)	-0.0049 (-1.41)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

about the anomalies and their interaction with risk factors or the mispricing factors is that in some cases, the sign of a significant hedging alpha points in the wrong direction compared to as predicted by previous literature, i.e. while the size anomaly's sign is consistent and firm size and returns are negatively related as predicted by literature, the investment anomaly's sign contradicts a similar negative relationship between investment level and expected returns. In some other cases, there are no significant differences to be found, contrary to what previous literature predicts about the existence of such anomalies. While there could be numerous reasons for these results in the entire period, such as poor factor quality, sensitivity to anomaly variable construction and calculation period, one in particular might stand out - time-series heterogeneity of anomaly portfolio returns and such returns' factor loadings.

5.3.1 Periodical estimation by factor models

The estimation period of 41 years between 1980 and 2020 is broken up into four sub-periods, 1980-89, 1990-99, 2000-09 and 2010-2020. For these four sub-periods, the same procedure is applied as before, such as the α -s of Table 8, Table 9 and Table 10 were estimated. Table 2 sums up the hedge portfolio α -s for the 14 anomalies in the 4 sub-periods as estimated by the CAPM, FF3 and FF5 models, which can also be found in Section 7.2, presented by Table 25 through Table 36. One of the key testing result is that with the occasional exception of the dividend yield anomaly, all three models for all 4 sub-periods and 13 anomalies provide a model with significant GRS-test result, suggesting that the periodical breakdown does not help the models to explain the decile portfolio returns and that all of the three models are inadequate asset pricing models for the 14 investigated anomalies. Even in the case of the dividend yield anomaly, this is most likely due to the lower number of firms per portfolio in the later sub-periods (post-2000), where each decile generally contains no more than 30 companies and might even drop as low as 7-8 companies per portfolio.

Even though the models fail in terms of the GRS-tests, the hedging portfolio α -s provide an interesting insight into the nature of the anomalies as well as the differences among the sub-periods. Another aspect of the breakdown of the entire sample period into sub-periods is to compare the oldest and newest periods specifically. The rationale behind this is that most of the investigated anomalies were first published upon in the 1990-2009 periods. [McLean & Pontiff \(2016\)](#) show that the portfolio returns for anomalies tend to be lower post-sample and especially post-publication, with the two effects summing up to as much as 56% lower anomaly returns. This effect becomes more pronounced after 1-2 years of the publication date. While this paper's aim is not to provide an event-study style analysis of anomaly returns pre- and post-publication, thus caution has to be taken when drawing conclusions, a comparison between the 1980-1989 and 2010-2020 sub-periods might confirm a pattern similar to the findings of [McLean & Pontiff \(2016\)](#).

The size anomaly is perhaps the most consistent pattern along the four sub-periods. While [Table 1](#) showed that small companies earn significantly higher returns than large companies throughout the entire period regardless of the factor model used for explaining the returns, the periodical breakdown shows another story. While the 1980-1989 period and the 2010-2020 period present significant anomaly returns, the significance decreases or even disappears altogether in the 1990-99 and 2000-09 sub-periods. More importantly, while the inclusion of the SMB (size) factor in models such as FF3 and FF5 can almost or completely reduce the anomaly hedge alpha to not significant result, this size factor fails to do the same in the '80s and '10s as in both periods, the two models estimate an average of 0.96-1.09% hedge excess return over the risk factors.

For the book-to-market anomaly, interestingly enough the CAPM only predicts the significant difference in the returns of high BM portfolio over low BM portfolio in the case of the 2000-09 period, where the CAPM hedge alpha implodes to above an average 2.6% (the same happens for the size anomaly in this period). However, while the inclusion of the HML factor based on the very same anomaly explains the returns post-2000, it creates a significant difference towards low BM companies before 2000, meaning that the estimation of the model predicts higher returns for lower BM portfolios, contradicting literature. While the operating profitability is relatively well explained by CAPM, the FF3 for the '80s predict a significant excess return of high over low profitability companies in line with the literature, but then a reverse of this in the case of the FF5 in the '90s. In general, however, the profitability anomaly's significance is rather weak and completely disappears post-2000. This picture is quite similar for the investment anomaly, where the CAPM predicts some significant returns of low investment companies over high investment companies in the '80s, the reverse applies for the FF5 in the '90s, after which period the anomaly seems to disappear altogether.

The dividend yield proves completely insignificant other than the 2010-2020 period, where the low dividend yield portfolio achieves much higher returns, as opposed to how literature predicts it. However, this difference might come from the low number companies in each decile portfolio, which raises doubts about sufficient diversification to cancel out any other risk source. On the other hand, the momentum anomaly is perhaps the most consistent anomaly across all four sub-periods, since almost exclusively the returns of the past winners exceed those of the past losers indicated by a negative α . Only the CAPM is capable of somewhat rendering the α -s across the four periods insignificant (3 out of 4), but this is more due to the variation in estimates and less due to its low magnitude. This same pattern applies for the entire period of 2000-2009, where average excess returns of high momentum over low momentum of 1.46% and 1.51% are not significant due to

variation in estimate. Nevertheless, the momentum anomaly’s presence is quite strong across the entire period.

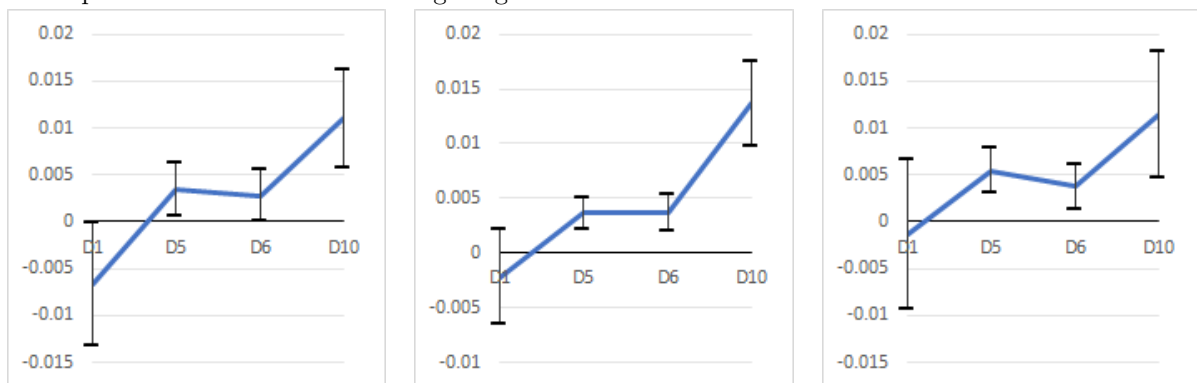
For the NETSTO, COMPEQ and ACCR anomalies, mostly the first period of 1980-1989 carry some significant hedge α -s with signs in line of the findings of previous literature. In the case of the accruals, this difference extends to the ’90s as well, but for the other two and subsequently post-2000 for all three of these anomalies, the significance disappears completely and mainly due to small magnitude of difference between D1 and D10. The same applies to the INVTOA anomaly as well, but on the other hand, the net operating assets anomaly only becomes visible after 1990. The net operating assets anomaly is perhaps the most prevalent across the time periods after the momentum anomaly, as its significance is present across models and periods post-1990 with strongly positive α -s.

On the other hand, the distress and the O-score anomalies present a similar pattern as estimated for the entire period of 1980-2020 by the various models in Table 1. Namely, both default probability anomalies tend to show that high default probability companies earn returns over low default probability ones, which goes contrary to the literature’s prediction. While the significance of these two anomalies are centered around the ’90s, other periods have relatively high D1-D10 spreads in magnitude, especially for the O-score, only rendered insignificant by the high variation as in the case of the momentum anomaly. Finally, the return on assets anomaly presents quite an interesting picture as well, since α -s are significantly positive in the ’80s, implying companies with more efficient usage of assets achieve higher returns than lower RETONA portfolios, which is in line with the literature’s prediction. However, this sign reverses over time and generally becomes negative for the 2010-2020 period, implying that over time, this anomaly reversed into the contrary of what literature would predict.

5.3.2 A word on the alpha patterns

Figure 1: Alpha patterns for MOM anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020



Examining the α patterns for the anomalies across the D1 to D10 deciles provides some insight about the trends in the anomaly and investigating the difference between the 1980-1989 and 2010-2020 periods shows the evolution of the anomalies over time. Table 2 presented that the hedge portfolio α -s estimated by the FF3 model change over time and the significance for the entire period as presented by Table 1 often disappear due to this heterogeneity between periods. Figure 1 shows the momentum anomaly α -s for

Figure 2: Alpha patterns for ACCR anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

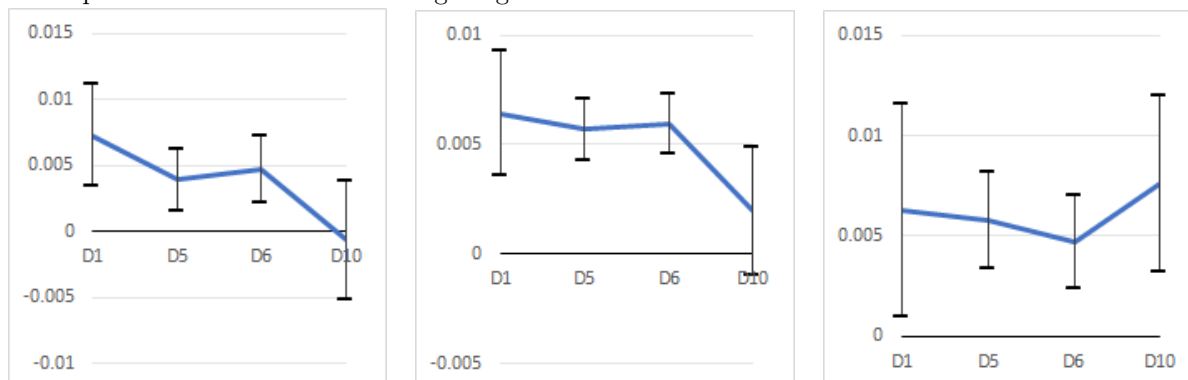
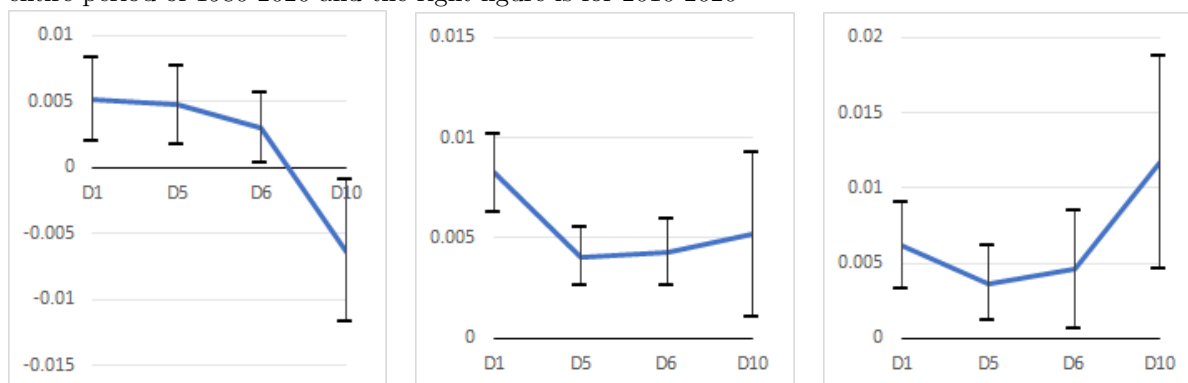


Figure 3: Alpha patterns for RETONA anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020



D1, D5, D6 and D10 for the 1980-1989, the entire 1980-2020 and the 2010-2020 periods. While the confidence intervals show greater variation for the two sub-periods than the entire period, the trend of the anomaly looks rather stable and monotone, even though the post-2010 period witnesses reduced distance across the decile α -s. This indicates that while some sophisticated traders may be exploiting the momentum anomaly in the post-2010 period through trading strategies, their impact on the market is not large enough to dissipate the momentum anomaly's effect. As the momentum anomaly has perhaps the weakest risk-based foundations, its prevalence across periods is the most puzzling phenomenon, especially if the slight reduction in the α -s for the post-2010 period is indeed due to traders exploiting the anomaly through hedging strategies. Similar patterns can be observed in the case of the size (Figure 6), net operating assets (Figure 13), and to a lesser extent, for the dividend yield (Figure 10) and net stock issuance (Figure 11)

On the other hand, the accruals anomaly presents a complete opposite of this picture depicted by the momentum anomaly. As Figure 2 shows, while the anomaly has a decreasing trend from D1 to D10 for the '80s and the hedge α is predicted to be significant by FF3 (Table 2). While the hedge for the anomaly in the entire 1980-2020 period is still slightly significant (Table 1), the excess returns over the FF3 factors are reduced by 35 basis points. The main reason for this reduction can be found in the right sub-figure of Figure 2, where the 2010-2020 sub-period shows that the D10 decile α is the highest

of all and the slightly decreasing monotone trend from D1 is disrupted. However, the anomaly simply disappears for the post-2010 period and the trend becomes inconsistent. A few other anomalies follow this pattern, such as the operating profitability (Figure 8), composite equity issuance (Figure 12) and to a lesser extent with the investment (Figure 9) and investment-to-assets anomalies (Figure 14).

Finally, the case of the return-on-assets anomaly shows that not only can anomalies disappear, but reverse completely as well. Figure 3 shows that the inconsistent pattern for the entire period is caused by the opposite trends in the '80s and the '10s. While the anomaly has a strong significance in the '80s as predicted by literature, namely highly profitable companies outperform low profitability companies, this pattern reverses to the opposite side post-2010. While the case of the Figure 2 and where the alpha patterns are reduced to similar levels in the post-2010 period indicates that the anomaly disappears due to either sophisticated traders crowding out the anomaly or the risk source disappearing altogether (which has a dubious plausibility), the case of reversal raises questions for both potential explanations. Intuitively, the explanation of sophisticated investors reducing the anomaly to insignificance would hardly hold in this case as this would mean that those sophisticated traders are consequently making a loss on these trading strategies. Alternatively, if the anomaly is indeed a representation of risk premia on portfolios with different risk exposures, the reversal of the risk premia sign over time offers little support for an underlying risk source as in this case, the implication would be that highly profitable companies carry higher and then lower risk throughout the different periods.

5.3.3 Periodical estimation by augmented factor models

After having looked at the periodical breakdown of alpha estimation on the anomaly hedge portfolios in Section 5.3.1, there seems to be a clear time-wise heterogeneity in the anomalies' significance and direction. Particularly interesting is the comparison between the 1980-1989 and 2010-2020 periods, since in the case of the BM, OP, INV, NETSTO, COMPEQ, ACCR, and INVTOA anomalies, there are significant differences estimated by at least of the three basic models in line with literature's prediction for the '80s, but all of these disappear by the post-2010 period. Furthermore, the return-on-assets anomaly, while predicted in the direction consistent with literature in the 1980-1989 period, reverses sign for the 2010-2020 period and goes opposite to what literature predicts. Out of the 14 anomalies, only 3 retains relatively consistent significance across periods and models, the size, the momentum and the net operating assets anomalies. However, does this picture change if one uses the augmented models for estimation to investigate whether the mispricing factors serve a better role in predicting returns in sub-periods?

Table 3 provides the insight into the SY-factor augmented models' performances in the different sub-periods. Compared to Table 2, there are some striking differences. Return-on-assets are briefly estimated to have a significant alpha and highly profitable companies earn higher risk-adjusted returns, but this only holds in the first sub-period and reverses again post-1990, indicating low return-on-assets companies subsequently achieve higher returns. The momentum anomaly's significance is completely erased over all sub-periods, but in some cases, this can be attributed to increased variance in estimates instead of lowering the α , and in the 1990-2010 periods, the insignificance is mainly due to the good performance of the models. Similarly, the inclusion of the SY-factor is strongly justified by the reduction in significance in the issuance anomalies (NETSTO and COMPEQ), and

Table 3: Alpha coefficients for anomaly hedge portfolios in augmented SY-factor models

	1980-1989			1990-1999			2000-2009			2010-2020		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
Size	0.0244*** (5.66)	0.0086*** (3.47)	0.0103*** (4.19)	0.0212*** (5.84)	0.0034 (1.34)	0.0028 (1.10)	0.0254*** (6.80)	0.0058 (1.90)	0.0069* (2.25)	0.0184*** (5.17)	0.0116*** (4.16)	0.0110*** (4.00)
BM	-0.0069 (-1.45)	0.0070* (2.46)	0.0061* (2.08)	-0.0068 (-1.43)	0.0024 (0.85)	0.0025 (0.87)	-0.0259*** (-4.21)	-0.0023 (-0.54)	-0.0017 (-0.41)	0.0013 (0.35)	0.0034 (1.12)	0.0034 (1.13)
OP	0.0067 (1.67)	-0.0054 (-1.31)	0.0024 (0.80)	0.0186*** (4.19)	0.0161*** (3.62)	0.0074* (2.12)	0.0052 (1.18)	0.0005 (0.14)	-0.0030 (-1.06)	0.0030 (1.36)	0.0016 (0.73)	0.0006 (0.29)
INV	0.0029 (0.92)	-0.0042 (-1.27)	-0.0019 (-0.65)	-0.0052 (-1.42)	-0.0075 (-1.94)	-0.0062* (-2.08)	0.0074 (1.84)	-0.0030 (-0.64)	0.0021 (0.63)	-0.0000 (-0.02)	-0.0009 (-0.31)	-0.0017 (-0.71)
DP	-0.0027 (-0.69)	-0.0012 (-0.29)	-0.0004 (-0.10)	-0.0078 (-1.88)	-0.0084 (-1.73)	-0.0044 (-0.90)	-0.0057 (-1.32)	-0.0071 (-1.33)	-0.0055 (-1.03)	0.0176** (2.66)	0.0175* (2.52)	0.0170* (2.48)
MOM	0.0102 (1.90)	0.0005 (0.10)	-0.0007 (-0.14)	-0.0037 (-0.56)	-0.0046 (-0.90)	-0.0008 (-0.16)	0.0007 (0.08)	-0.0063 (-0.86)	-0.0048 (-0.64)	-0.0105 (-1.93)	-0.0108 (-1.96)	-0.0093 (-1.82)
NETSTO	0.0008 (0.33)	-0.0034 (-1.21)	-0.0045 (-1.60)	-0.0017 (-0.52)	0.0033 (0.95)	0.0052 (1.46)	0.0040 (1.35)	-0.0002 (-0.05)	0.0004 (0.11)	0.0018 (0.71)	0.0025 (0.96)	0.0033 (1.32)
COMPEQ	-0.0018 (-0.53)	0.0025 (0.64)	-0.0005 (-0.14)	-0.0049 (-1.62)	-0.0017 (-0.50)	-0.0007 (-0.21)	-0.0024 (-0.57)	-0.0006 (-0.13)	-0.0022 (-0.45)	-0.0003 (-0.09)	-0.0001 (-0.04)	-0.0001 (-0.04)
ACCR	-0.0038 (-1.14)	0.0000 (0.01)	0.0021 (0.57)	0.0034 (0.83)	0.0095* (2.08)	0.0092* (2.02)	-0.0039 (-0.98)	-0.0026 (-0.52)	-0.0023 (-0.48)	-0.0027 (-0.79)	-0.0017 (-0.50)	-0.0018 (-0.51)
NETOPA	-0.0020 (-0.74)	-0.0021 (-0.67)	-0.0004 (-0.14)	0.0027 (0.64)	0.0087 (1.97)	0.0065 (1.44)	0.0066 (1.56)	0.0106* (2.49)	0.0101* (2.37)	0.0090** (3.15)	0.0080** (2.80)	0.0078** (2.79)
INVTOA	0.0019 (0.70)	-0.0062* (-2.29)	-0.0030 (-1.21)	0.0006 (0.20)	0.0012 (0.34)	0.0011 (0.33)	0.0022 (0.66)	-0.0015 (-0.39)	-0.0010 (-0.28)	-0.0007 (-0.25)	-0.0020 (-0.69)	-0.0025 (-0.96)
DISTRESS	-0.0101* (-2.28)	-0.0076 (-1.45)	-0.0068 (-1.33)	-0.0066 (-1.88)	-0.0105** (-2.63)	-0.0107* (-2.55)	-0.0039 (-0.71)	-0.0039 (-0.58)	-0.0017 (-0.25)	-0.0066 (-1.53)	-0.0032 (-0.75)	-0.0032 (-0.79)
OSCORE	-0.0103* (-2.39)	0.0030 (1.05)	-0.0013 (-0.52)	-0.0295*** (-4.71)	-0.0191*** (-4.14)	-0.0149** (-3.32)	-0.0170 (-1.92)	-0.0103 (-1.77)	-0.0132** (-2.73)	-0.0103* (-2.26)	-0.0037 (-0.86)	-0.0020 (-0.51)
RETONA	-0.0049 (-1.22)	0.0094* (2.46)	0.0036 (1.14)	-0.0133** (-3.28)	-0.0099* (-2.22)	-0.0051 (-1.27)	-0.0067 (-1.25)	-0.0042 (-0.91)	-0.0051 (-1.22)	-0.0127*** (-3.70)	-0.0081* (-2.50)	-0.0071* (-2.28)

t statistics in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

works better for the accruals and investment-to-assets anomalies, albeit some significance remains for the latter two. Nevertheless, a similar pattern emerges with the inclusion of the SY-factor as in Table 1 for the two default-probability anomalies (distress and O-score), namely that the inclusion of the factor creates significantly negative α -s in more cases than without the factor, estimating a significant return of distressed companies over financially stable companies. Furthermore, the factor changes very little for the anomalies not involved in its construction, so the Size, BM, OP, INV and DP anomalies.

Table 4 shows the same procedure with the BG-factor and the robustness of this factor is again investigated by its simulative version, the TSBG-factor in Table 41. The results show a similar trend as with the SY-factor, namely that while the augmented versions might make some small improvements to the model, overall their effectiveness is highly ambiguous. The BG-factor is unable to reduce the significance of the momentum anomaly consistently, although it does reduce significance for the post-2000 periods, this is most likely due to increase in variation and less due to efficient pricing. Similarly, there is little difference in the performance of the basic models of Table 2 and their BG-factor and TSBG-factor augmented versions for the accruals, net operating assets, book-to-market, size or profitability anomalies. However, there is a recognisable difference between the performance of the TSBG-factor augmented models and the base or BG-factor models for a few anomalies, such as the investment, the issuance anomalies (net stock issues and composite equity issues) or the investment-to-assets. In these cases, the TSBG-factor augmentation works rather well, especially in the 1980-1989 period due to reduction in α -s, which could indicate that these anomalies were significant due to mispricing effects rather than some underlying risk source. Furthermore, the two Bartram-Grinblatt mispricing factors might cope with the default anomalies as well as the return on assets anomaly, as while there might be some significant α -s still, their significance tends to disappear post-2000, something which is not necessarily the case for Table 2 or Table 3.

Table 4: Alpha coefficients for anomaly hedge portfolios in augmented BG-factor models

	1980-1989			1990-1999			2000-2009			2010-2020		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
Size	0.0188*** (4.77)	0.0096*** (4.79)	0.0100*** (4.45)	0.0139*** (3.58)	0.0047* (2.17)	0.0034 (1.65)	0.0257*** (6.54)	0.0055 (1.80)	0.0056 (1.81)	0.0150*** (3.86)	0.0097*** (3.51)	0.0099*** (3.58)
BM	0.0018 (0.58)	0.0063** (2.84)	0.0064* (2.48)	-0.0026 (-0.71)	0.0059* (2.45)	0.0062* (2.61)	-0.0188*** (-4.23)	-0.0009 (-0.20)	-0.0005 (-0.12)	-0.0012 (-0.31)	0.0026 (0.86)	0.0026 (0.91)
OP	-0.0021 (-0.56)	-0.0096** (-2.88)	-0.0009 (-0.32)	0.0073 (1.61)	0.0025 (0.59)	0.0061* (2.07)	0.0096* (2.09)	-0.0024 (-0.56)	-0.0035 (-1.23)	0.0010 (0.44)	-0.0003 (-0.14)	0.0002 (0.09)
INV	0.0063* (2.20)	0.0042 (1.45)	-0.0019 (-0.70)	-0.0002 (-0.06)	0.0002 (0.05)	-0.0053* (-2.14)	0.0073 (1.62)	-0.0005 (-0.10)	0.0016 (0.50)	0.0014 (0.46)	0.0010 (0.33)	0.0000 (0.01)
DP	0.0006 (0.19)	0.0030 (0.98)	0.0040 (1.12)	-0.0054 (-1.35)	-0.0042 (-1.01)	-0.0047 (-1.15)	-0.0060 (-1.32)	-0.0044 (-0.77)	-0.0035 (-0.66)	0.0149* (2.20)	0.0161* (2.35)	0.0165* (2.40)
MOM	-0.0125** (-2.83)	-0.0175*** (-4.06)	-0.0110* (-2.29)	-0.0103 (-1.92)	-0.0180*** (-3.73)	-0.0161** (-3.29)	-0.0089 (-1.24)	-0.0084 (-0.95)	-0.0098 (-1.19)	-0.0044 (-0.80)	-0.0085 (-1.67)	-0.0086 (-1.67)
NETSTO	0.0047* (1.99)	0.0035 (1.47)	-0.0026 (-1.03)	0.0018 (0.61)	0.0048 (1.65)	0.0045 (1.50)	0.0027 (0.87)	0.0040 (1.03)	0.0047 (1.31)	0.0037 (1.45)	0.0044 (1.73)	0.0040 (1.61)
COMPEQ	0.0042 (1.33)	0.0075* (2.38)	-0.0003 (-0.09)	0.0004 (0.13)	0.0037 (1.27)	0.0034 (1.17)	-0.0005 (-0.13)	-0.0015 (-0.29)	-0.0016 (-0.33)	0.0013 (0.38)	0.0025 (0.70)	0.0027 (0.77)
ACCR	0.0047 (1.45)	0.0079* (2.58)	0.0058 (1.70)	0.0080* (1.98)	0.0121** (3.10)	0.0098* (2.56)	-0.0044 (-1.06)	-0.0009 (-0.17)	-0.0001 (-0.02)	-0.0016 (-0.47)	-0.0006 (-0.18)	-0.0005 (-0.14)
NETOPA	0.0030 (1.17)	0.0049 (1.90)	0.0043 (1.46)	0.0075 (1.77)	0.0135*** (3.51)	0.0141*** (3.57)	0.0096* (2.54)	0.0126** (2.88)	0.0129** (3.04)	0.0078** (2.69)	0.0076** (2.65)	0.0082** (2.91)
INVTOA	0.0057* (2.35)	0.0039 (1.56)	0.0012 (0.51)	0.0037 (1.20)	0.0050 (1.56)	0.0015 (0.56)	0.0032 (0.95)	0.0001 (0.03)	0.0008 (0.20)	-0.0001 (-0.04)	-0.0007 (-0.23)	-0.0018 (-0.67)
DISTRESS	-0.0022 (-0.53)	-0.0001 (-0.01)	-0.0000 (-0.00)	-0.0061 (-1.82)	-0.0080* (-2.39)	-0.0079* (-2.32)	-0.0064 (-0.92)	0.0019 (0.23)	0.0038 (0.54)	-0.0058 (-1.06)	-0.0005 (-0.10)	-0.0004 (-0.08)
OSCORE	-0.0056 (-1.45)	0.0025 (1.10)	-0.0019 (-0.85)	-0.0131* (-2.36)	-0.0050 (-1.15)	-0.0069 (-1.77)	-0.0272*** (-3.79)	-0.0068 (-1.13)	-0.0074 (-1.41)	-0.0018 (-0.41)	0.0029 (0.80)	0.0023 (0.64)
RETONA	0.0039 (1.11)	0.0115*** (3.73)	0.0071* (2.43)	-0.0035 (-0.81)	0.0019 (0.47)	0.0013 (0.38)	-0.0117 (-1.91)	-0.0013 (-0.22)	-0.0007 (-0.13)	-0.0065 (-1.67)	-0.0023 (-0.70)	-0.0028 (-0.85)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4 GRS-test results for hedge portfolios only

While the GRS-test yields significant results on the intra-anomaly portfolio pricing of every model (base models and their augmented versions as well) for the sub-periods as well as the entire period, there might be an alternative way of testing the models' capabilities to explain the anomalies. The intra-anomaly GRS-tests test whether the decile portfolio α -s for any given anomaly and period are explained adequately by the factors in the factor model. On the other hand, one might be more interested in the models' ability to explain the long-short spread α -s for the anomalies, as [Stambaugh & Yuan \(2017\)](#) also investigate in their paper. For this reason, the authors investigate each model's ability to jointly price the anomalies' hedge portfolio α -s correctly. In a similar approach, [Table 5](#) produces the GRS-test results for each of the sub-periods and the entire period as well for all of the 14 anomalies investigated so far in the paper. The table basically follows the outline of [Table 1](#), where the first column group represents 3 models, the CAPM, the FF3 and the FF5 models, or in the case of the mispricing factor column groups, these models' augmented versions.

Table 5: GRS F-tests for anomaly hedge portfolio alphas in all models and periods

	Base models			Augmented SY			Augmented BG			Augmented Theil-Sen median BG		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
1980-1989	14.80*** 0.000	12.95*** 0.000	6.53*** 0.000	12.84*** 0.000	5.19*** 0.000	4.86*** 0.000	15.17*** 0.000	12.51*** 0.000	6.44*** 0.000	15.44*** 0.000	10.91*** 0.000	6.33*** 0.000
1990-1999	2.53** 0.004	4.01*** 0.000	4.62*** 0.000	5.09*** 0.000	3.86*** 0.000	3.02*** 0.001	2.65** 0.002	3.89*** 0.000	4.63*** 0.000	2.46** 0.005	3.74*** 0.000	4.35*** 0.000
2000-2009	5.55*** 0.000	1.81* 0.046	1.78 0.052	6.54*** 0.000	2.33** 0.008	2.12* 0.016	5.24*** 0.000	1.78 0.051	1.73 0.061	5.40*** 0.000	1.54 0.109	1.43 0.152
2010-2020	3.37*** 0.000	2.63** 0.002	3.05*** 0.001	3.52*** 0.000	2.64** 0.002	2.89*** 0.001	2.73** 0.002	2.37** 0.006	2.78** 0.001	2.61** 0.003	1.99* 0.024	2.23* 0.011
1980-2020	12.58*** 0.000	7.70*** 0.000	7.46*** 0.000	16.41*** 0.000	6.92*** 0.000	6.87*** 0.000	12.79*** 0.000	7.64*** 0.000	7.28*** 0.000	12.39*** 0.000	7.21*** 0.000	6.50*** 0.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

What is clear from Table 1, that the factor models are not capable of pricing the hedge portfolios quite effectively in general is confirmed by the GRS-test results for the 1980-2020 period. The factor models practically fail to price the 14 anomalies at the same time and adding any of the previously constructed mispricing factors to the models does not help this case. However, the decade-wise breakdown of the estimation period provides extra insight into the nature of the anomalies. As observed before, the anomalies are more prevalent in the '80s and the '90s, albeit the ordinary CAPM and the BG-factor and TSBG-factor augmented versions of the model obtain a relatively lower (but still significant at 1% level) F-statistic for the GRS test.

On the other hand, the post-2000 period shows interesting results regarding the models' hedge pricing capabilities. For the 2000-2009 period, the FF3 and FF5 models come closer or even achieve insignificant test results, suggesting they might be valid and explain the α -s well for this sub-period. Interestingly, while the SY-factor is counterproductive in explaining hedges overall, both versions of the BG-mispricing factor help reducing the F-statistic to insignificance. Still, the reduction might be more due to the period specificity and the addition of the SMB or HML factors, since the base models produce very similar results. This pattern on the other hand does not apply so much in the 2010-2020 period. While all of the models have statistically significant GRS-results, the significance on the BG and TSBG augmented versions are lower, and the F-stats of the CAPM+BG-factor and CAPM+TSBG-factor are similar in magnitude to the base FF3 and FF5 models, which might suggest that the mispricing factors are just as successful in explaining hedge α -s as the Fama & French (2015) risk factors. Nevertheless, most GRS-tests are still significant and the post-2000 periods' vanishing GRS-test significance is most likely due to vanishing anomalies rather than better factor model performance.

5.5 Anomalies in the fair-valued universe of stocks

There is relatively weak evidence of the mispricing factors to bear considerable explanatory power towards the anomalies and it does not seem to improve the traditional factor models too much. The mispricing factors are somewhat more powerful in a decade-wise breakdown as seen in Section 5.3 and might even be as useful as the CMA and RMW factors in some cases, but the overall picture shows that mispricing might have relatively heterogeneous effects on these anomalies and hence one mispricing factor is inadequate to explain all anomalies at the same time. However, a different approach is applied by Stambaugh & Yuan (2017), who construct their small-minus-big (SMB) size factor on the plain of fair priced equities only. They find that the explanatory power of such a factor increases enormously, indicating that mispricing adds noise for the size risk factor rather than explaining it. Obviously, such an approach has to be taken with care, since including only fair-valued stocks in the anomaly portfolios might alter the composition of the portfolio in terms of the anomaly variable. Since this alteration in the anomaly variable structure of the decile portfolios is more likely to happen with the SY-variable, since this mispricing variable is constructed using the ranks of the stocks for each of the anomalies, such a portfolio sorting is the most suitable with the Bartram & Grinblatt (2018) mispricing measure.

Table 6 contains the hedge portfolio α -s in the setup similar to Table 2, but these decile portfolios and consequently the D1-D10 hedge portfolio were sorted by including only fair-valued companies according to the BG mispricing variable. Namely, as the BG-factor's setup is described in Equation (8) where the undervalued 20% and the overvalued

Table 6: Alpha coefficients for anomaly hedge portfolios in the BG fair-valued plain

	1980-1989			1990-1999			2000-2009			2010-2020		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
Size	0.0126** (2.95)	0.0013 (0.67)	0.0021 (1.04)	0.0149** (3.37)	0.0037 (1.71)	0.0032 (1.45)	0.0264*** (5.67)	0.0063 (1.93)	0.0064 (1.93)	0.0120** (3.34)	0.0045* (2.03)	0.0044* (1.98)
BM	-0.0043 (-1.04)	0.0063* (2.37)	0.0042 (1.35)	-0.0030 (-0.62)	0.0051 (1.52)	0.0038 (1.26)	-0.0145* (-2.54)	0.0042 (0.80)	0.0045 (0.98)	0.0033 (0.91)	0.0062 (1.98)	0.0067* (2.18)
OP	-0.0017 (-0.40)	-0.0094* (-2.31)	0.0020 (0.57)	0.0056 (1.20)	0.0000 (0.01)	0.0029 (1.01)	0.0032 (0.51)	-0.0036 (-0.69)	-0.0038 (-0.84)	0.0033 (1.39)	0.0013 (0.54)	0.0009 (0.40)
INV	0.0047 (1.46)	0.0002 (0.06)	-0.0051 (-1.65)	-0.0005 (-0.16)	0.0026 (0.79)	-0.0011 (-0.40)	0.0078 (1.51)	0.0012 (0.19)	0.0020 (0.45)	0.0012 (0.35)	0.0024 (0.70)	0.0011 (0.39)
DP	0.0037 (1.03)	0.0066 (1.77)	0.0041 (0.93)	-0.0044 (-0.91)	-0.0034 (-0.68)	-0.0042 (-0.84)	0.0044 (0.94)	0.0061 (1.07)	0.0063 (1.11)	0.0159* (2.24)	0.0136 (1.87)	0.0141 (1.92)
MOM	-0.0094 (-1.83)	-0.0188*** (-4.02)	-0.0119* (-2.28)	-0.0125 (-1.96)	-0.0160** (-2.94)	-0.0145* (-2.62)	-0.0031 (-0.32)	-0.0119 (-1.21)	-0.0124 (-1.33)	-0.0098 (-1.75)	-0.0118* (-2.09)	-0.0115* (-2.03)
NETSTO	0.0066* (2.21)	0.0029 (1.01)	-0.0038 (-1.21)	0.0005 (0.13)	0.0021 (0.62)	0.0017 (0.51)	0.0036 (0.93)	0.0036 (0.77)	0.0039 (0.85)	0.0026 (1.08)	0.0035 (1.39)	0.0039 (1.57)
COMPEQ	0.0056 (1.51)	0.0097* (2.52)	-0.0003 (-0.08)	-0.0028 (-0.76)	0.0024 (0.71)	0.0014 (0.44)	-0.0028 (-0.55)	0.0020 (0.36)	0.0019 (0.36)	0.0030 (0.84)	0.0045 (1.25)	0.0046 (1.27)
ACCR	0.0073 (1.97)	0.0125** (3.32)	0.0072 (1.71)	0.0059 (1.45)	0.0098* (2.43)	0.0056 (1.51)	-0.0045 (-1.03)	-0.0012 (-0.22)	-0.0007 (-0.15)	-0.0014 (-0.40)	-0.0000 (-0.01)	-0.0001 (-0.02)
NETOPA	0.0048 (1.59)	0.0065* (2.05)	0.0053 (1.50)	0.0080 (1.52)	0.0141** (3.21)	0.0150** (3.32)	0.0060 (1.26)	0.0123* (2.53)	0.0124* (2.55)	0.0102** (3.13)	0.0108** (3.25)	0.0110*** (3.39)
INVTOA	0.0089** (2.86)	0.0058 (1.77)	0.0034 (1.02)	0.0044 (1.21)	0.0075* (2.04)	0.0042 (1.20)	0.0007 (0.17)	0.0002 (0.05)	0.0004 (0.10)	0.0009 (0.32)	0.0011 (0.37)	0.0003 (0.12)
DISTRESS	-0.0041 (-0.97)	-0.0028 (-0.62)	0.0001 (0.01)	-0.0040 (-1.06)	-0.0046 (-1.19)	-0.0040 (-1.01)	-0.0008 (-0.13)	0.0013 (0.17)	0.0018 (0.29)	-0.0040 (-0.94)	0.0008 (0.19)	0.0010 (0.23)
OSCORE	-0.0043 (-1.22)	0.0027 (0.99)	-0.0021 (-0.70)	-0.0133* (-2.31)	-0.0030 (-0.73)	-0.0042 (-1.22)	-0.0225* (-2.22)	-0.0106 (-1.66)	-0.0109 (-1.93)	-0.0043 (-1.07)	0.0033 (1.06)	0.0036 (1.35)
RETONA	-0.0009 (-0.27)	0.0050 (1.45)	0.0032 (0.91)	0.0053 (1.23)	0.0091* (2.14)	0.0101** (2.71)	-0.0071 (-0.93)	0.0001 (0.02)	0.0000 (0.01)	-0.0039 (-0.97)	0.0011 (0.29)	0.0015 (0.41)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

20% are used, in this sorting only the fair-valued 60% (Q2 through Q4) are used to sort the stocks into 10 decile portfolios based on the anomaly variable.

Comparing the results of Table 6 with the results previously seen in Section 5.3, there are some interesting results. The exclusion of the most mispriced stocks reduces the magnitude and the significance of the size anomaly across all periods. However, the significance does not disappear all the time, this mostly happens when the size factor is in the model, suggesting that the size risk factor does indeed work on its own anomaly if noise is removed from the anomaly. The significance of the return-on-assets anomaly for the '80s is also reduced, but on the other hand, this significance now appears in the '90s. Apart from these two anomalies, there are not many significance changes in the others, but the α coefficient estimates are changed typically in a strange pattern once again along period lines. While the pre-2000 periods generally exhibit increased magnitude α -s compared to those seen in Table 2, the opposite applies for the post-2000 periods. This suggests that by removing the most mispriced stocks from the universe of stocks used for portfolio sorting, most anomalies' hedge α -s become larger in magnitude for the 1980-1999 sub-periods while these same hedge α -s stay the same or even decrease in absolute value for 2000-2020. This could mean that while some of these anomalies were in fact real anomalies in the pre-2000 periods due to significant difference in the returns of one extreme portfolio over another, creating a market-neutral trading opportunity, most anomalies in the post-2000 period do not represent trading opportunities and might exist due to market mispricing rather than some underlying risk explanation. These results are practically the same using the Theil-Sen median version of the BG mispricing signal, described in Table 40.

Table 7: Alphas for the mispricing hedges estimated for different periods

	1980-1989			1990-1999			2000-2009			2010-2020			1980-2020		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
SY	0.0062* (2.35)	0.0125*** (5.39)	0.0042 (1.96)	0.0032 (1.04)	0.0095*** (4.02)	0.0068*** (3.72)	-0.0010 (-0.26)	0.0066 (1.49)	0.0071* (2.20)	0.0009 (0.32)	0.0055* (2.39)	0.0053* (2.41)	0.0032* (2.04)	0.0095*** (6.44)	0.0063*** (5.22)
BG	0.0040 (1.35)	-0.0034 (-1.37)	-0.0017 (-0.60)	-0.0012 (-0.35)	-0.0032 (-1.52)	-0.0028 (-1.33)	0.0137** (3.14)	-0.0043 (-1.31)	-0.0044 (-1.31)	-0.0049 (-1.84)	-0.0018 (-0.73)	-0.0015 (-0.66)	0.0017 (0.99)	-0.0014 (-0.95)	-0.0016 (-1.06)
TSBG	0.0091** (3.08)	0.0015 (0.78)	-0.0015 (-0.72)	-0.0041 (-0.83)	-0.0053 (-1.79)	-0.0057 (-1.96)	0.0125* (2.12)	-0.0093* (-2.54)	-0.0094* (-2.55)	-0.0090* (-2.60)	-0.0091** (-3.04)	-0.0089*** (-3.55)	0.0016 (0.69)	-0.0041** (-2.61)	-0.0056*** (-3.67)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.6 Mispricing as an anomaly itself

So far the results present that only some of the investigated anomalies are in fact real anomalies and some others only show up occasionally as estimated by the traditional factor models and the mispricing factors. However, the mispricing factors have relatively weak explanatory power on the anomalies in general and these factors become important in explaining returns only when their information is specific for the given anomaly. The definition of the estimation period seems to matter the most as other than the size or the momentum anomalies, most anomalies vary in sign and significance over time, hence they do not present clear trading opportunities. Subsequently, the question arises whether portfolios sorted on levels of mispricing create a trading opportunity as a stock market anomaly. The hypothesis on efficient markets predicts that mispricing should not occur in the first place and even if it does, it should be a random noise and not a consistent trend. Despite mispricing not being the cause for many cross-sectional anomalies' existence, a consistent anomaly based on buying underpriced and selling overpriced stocks could undermine the hypothesis of efficient markets since such an anomaly should quickly be off-set by sophisticated traders and the market's long-term convergence towards fair valuation.

Table 7 presents the hedge portfolio α -s estimated by the three base models on the mispricing variables of SY, BG and the latter's Theil-Sen median version. The results show the clear disparity between the [Stambaugh & Yuan \(2017\)](#) and the [Bartram & Grinblatt \(2018\)](#) methodologies. As mentioned previously, the correlation between the mispricing factors themselves is rather insignificant with a 0.09 correlation coefficient. While the mispricing hedges are not entirely the same as the factors (size-median separation is not applied), the patterns of excess returns on these portfolios also show a great disparity. Therefore, the conclusion must be drawn that the difficult challenge of quantifying mispricing is approached by two different methodologies by the two factors.

The SY-mispricing portfolios produce a relatively constant and significant positive α across sub-periods, indicating that undervalued stocks consistently outperform overvalued stocks. As the mispricing measure is constructed from 11 anomaly rankings, most of which are present in the analysis before, the α -s seem to follow the same pattern, that is the difference between long and short legs is stronger in the pre-2000 sub-periods and while still often significant in the post-2000 sub-periods, the spread becomes lower in magnitude. Even more telling is the pattern that the CAPM model actually outperforms the FF3 and FF5 models in relative explanatory power over the SY mispricing. Throughout most sub-periods and the entire 1980-2020 period, the CAPM either renders the α insignificant or estimates a small magnitude. However, when the different risk factors are appended to market excess returns, the α -s become largely positive and more significant. This indicates that undervalued stocks have significantly higher risk-adjusted returns than overvalued stocks, which are not contained in the three-factor and five-factor models.

Figure 4: The persistence of the SY hedge alpha significance as estimated by FF3

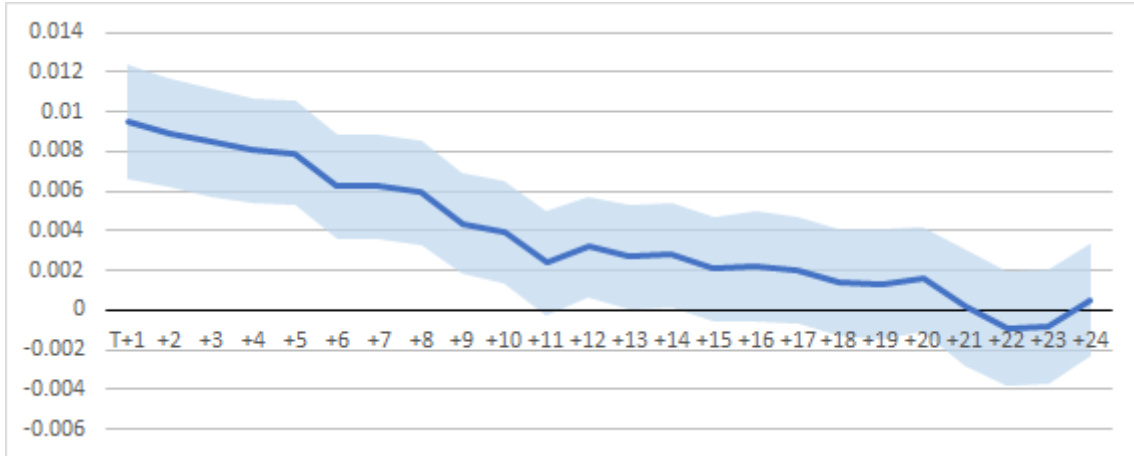
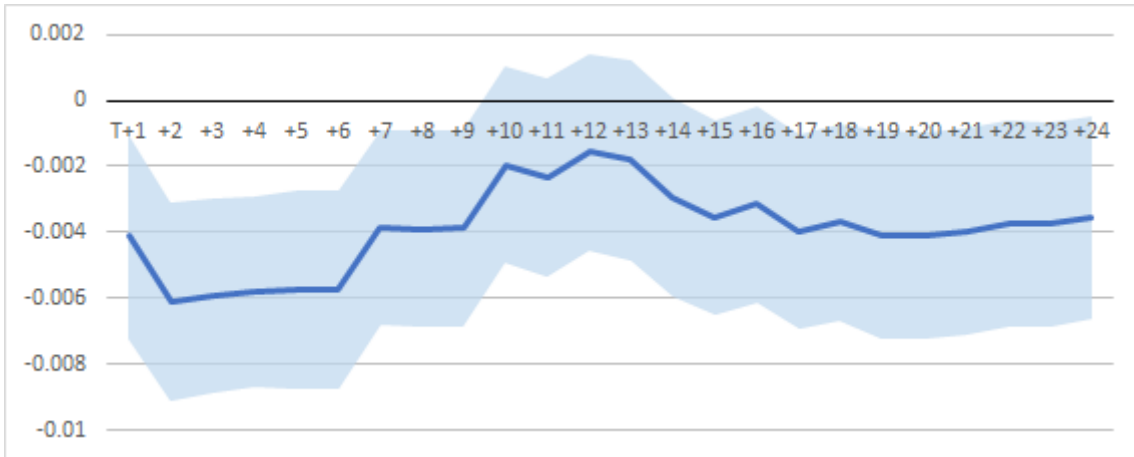


Figure 5: The persistence of the TSBG hedge alpha significance as estimated by FF3



On the other hand, the [Bartram & Grinblatt \(2018\)](#) mispricing variable creates quantile portfolios which are by far not significant. Except for the 2000-2009 period estimated by CAPM, there is no fundamental difference between the returns of undervalued and overvalued stock portfolios. However, the Theil-Sen median of this variable creates a significant difference between the two mispriced legs mostly in the post-2000 periods as well as the whole, albeit with a reversed sign. This implies the very opposite of the [Stambaugh & Yuan \(2017\)](#) measure, namely that overvalued stocks outperform undervalued stocks. However, this is mainly estimated by the same FF3 and FF5 models which are unable to accommodate the SY mispricing anomaly either, since on the other hand, the CAPM predicts the hedge in the other direction, suggesting that it is the undervalued portfolio which outperforms the overvalued one.

The persistence of the significant α -s on mispricing portfolios also testify about the mispricing phenomenon in the market. In the case of Figure 4, the undervalued stocks identified by the SY-variable continue to outperform overvalued stocks significantly for approximately a year after the portfolio formation as predicted by the FF3 model. On the other hand, the Theil-Sen BG-variable brings approximately the same results with the opposite sign as shown in Figure 5 in the FF3 model. Similar to the pattern seen in Table 7, the ordinary BG-variable produces mostly insignificant hedge α -s and these are persistent over time (Figure 17), i.e. the BG-variable does not create portfolios with

significantly different returns.

5.7 Reconciliation of findings with previous literature

The results of this paper mostly contradict the evidence presented by previous literature before, or at least fail to find such compelling evidence for the consistency of anomalies, the explanatory power of mispricing factors, etc. While there could be numerous different reasons for these contradictions and pinpointing the exact reasons by substantiating with clear evidence is beyond the scope of the paper, the results offer some likely explanations, which may offer further insight into the nature of the anomalies and the role of mispricing.

While the methodology of handling accounting variables and setting up the anomaly variables are described in Section 7.1 and Section 4.2 and the use of variables as defined by previous literature are closely followed with very small modifications (all described under their respective methodologies), one thing which may differ is the point-in-time at which accounting data is considered public and can be used for creating the anomaly variable. For example, while Fama & French (2015) set up the anomaly variables by only one sorting per year where accounting data from the previous year is used 6 months after for sorting and 7 months after for returns, this paper uses a more complex method of obtaining the accounting variables as described by Section 7.1.1, which updates the release of the information on a monthly basis and typically the release date occurs 5 months after the financial period end (or in case the release date is not available, 6 months after). This might in fact cause differences between the anomalies' significance and persistence, which would imply that the market is generally slower than 1-2 months to incorporate newly released accounting information into the pricing. Furthermore, it could explain why the size and the momentum anomalies are perhaps the most persistent in this paper across separate models and periods, since these variables do not rely on accounting data. However, Stambaugh & Yuan (2017) use a very similar methodology and yet some of the anomalies from their mispricing measure, such as the net operating assets, distress & O-score or return on assets are relatively persistent as well. Besides, the most insignificant anomalies are in fact those without accounting variables as well, such as the dividend yield or the composite equity issuance.

One more difference in the results could be the small deviations in the use of variables to obtain the mispricing measures as well as some of the anomalies. Namely, both the BG and the SY measures (and subsequently the anomalies used for the SY-measure construction) are very slightly different than the original methodologies, mostly due to data availability. For example, the distress score variables are slightly different than described by Stambaugh & Yuan (2017), and for the BG mispricing signal, two of the 28 original accounting variables had to be omitted due to data unavailability (Section 7.1.1). Yet this is very unlikely to be the source of difference between the results and Bartram & Grinblatt (2018) describe themselves that the explanatory variables for predicting mispricing are highly correlated and hence can explain each other, effectively taking on the explanatory power of one another. Furthermore, the results of the paper are robust to using the original two SY-mispricing factors (PERF and MGMT) or the Fama & French (2015) five factors available in online databases of the authors for the analyses of the paper, such as the hedge alpha prediction or the GRS-tests of models pricing the hedge portfolios jointly. Hence, these alternative explanations likely explain a small part of the differences between the results of this paper and those of the previous literature.

This leaves little other explanation for the discrepancy than the time periods for es-

timation. The results suggest that anomaly significance, persistence and factor model performance depends strongly on how the estimation time periods are defined. Unfortunately, due to data unavailability, it is rather difficult to test this, but the results of heterogeneous α -s as well as their significance in the sub-periodical breakdown suggest that anomalies are not consistent over time and their sign as well as their magnitude depends strongly on which estimation period one chooses. This applies to factor models as well, since GRS-tests and hedge α -s imply that factor models perform better in some sub-periods, especially in periods where the anomalies explained by these models are already well-known to the market.

Avenues for future research could investigate the mispricing factors' impact on a wider range of anomalies and specifically beyond the types of anomalies investigated by [Stambaugh & Yuan \(2017\)](#) since that paper mainly looks into the anomalies connected to stock characteristics, profitability and investment levels. Alternatively, different mispricing methodologies could be utilised which might be better suited for explaining cross-sectional anomalies, however, the difficulty of objectively identifying and measuring mispricing will inherently present a great hurdle. Fintech tools such as machine learning techniques and models might also offer a more accurate identification of mispricing information in stock returns. However, it would seem that many cross-sectional anomalies identified by literature are less economically significant and sensitive to anomaly variable and estimation period definitions, hence future research should perhaps focus on identifying and separating real anomalies from those that are temporary and which present no clear and consistent trading opportunities.

6 Conclusion

While the results on explaining anomaly returns with different factor models and their mispricing factor augmented versions might seem mixed, it would seem that apart from a few anomalies examined in this paper, such as the size, momentum or net operating assets, most anomalies do not provide consistent and significant trading opportunities. Most anomalies are sensitive to estimation period definition and their signs and significance varies over time. Anomalies such as the size, momentum or net operating assets anomalies are strongly significant and consistent in their sign over different periods and factor models, indicating that these might in fact present viable trading strategies. The mispricing factors offer little help in explaining these anomalies with the notable exception of the SY-factor which may reduce the significance of the momentum and net operating assets anomalies.

On the other hand, most of the other anomalies are only significant and consistent with previous literature in the 1980-89 sub-period and disappear or reverse altogether after 2000, indicating that the market's awareness post-publication might help eliminating these anomalies. However, this could also be due to better model performance, which might in turn be due to the adoption of the factor models as a standard to estimate expected returns and to price the anomalies, leading to the disappearance of the anomalies only in the framework of such risk models. However, evidence implies that many of the investigated anomalies disappear and might re-emerge or reverse and this pattern is period-specific (for example lowest significance of GRS-tests for the 2000-2009 period and α pattern differences from D1 to D10) rather than factor-model specific.

Furthermore, the inclusion of mispricing signals in factor models offers inconclusive

evidence on whether these anomalies are explained by risk factors or market sentiment and behavioural factors leading to mispricing. While in some cases, mispricing factors work better than risk factors (especially the addition of the CMA and RMW factors), such as the ability of the SY-factor to reduce hedge α -s on some anomalies to insignificance and the occasional improvement in GRS-tests by the inclusion of the (Theil-Sen median) BG-factor, these are only partial results and might depend on the definition of the time period as well. On the other hand, removing the highly mispriced stocks from the anomaly portfolio sorting seems to have very little effect on the significance of the anomalies, albeit the anomalies sorted only on the fair-valued stocks by the BG and TSBG mispricing signals tend to decrease slightly in magnitude and significance for the pre-2000 periods and increase for the post-2000 periods.

Besides, the improvement brought by the SY-factor is almost exclusive to the anomalies assisting in the factor's construction and similar improvement cannot be observed by the BG and TSBG factors. Additionally, the low correlation between the mispricing factors further cements the notion that these mispricing factors tell different stories about actual mispricing and its effect on anomalies, suggesting that while it might be possible to create anomaly specific mispricing factors and use them to price similar anomalies, there is no universal way of constructing one mispricing factor which is able to accommodate the potential mispricing component of all anomalies at the same time. Furthermore, the potential improvement in the factor model's ability to price anomalies brought by the mispricing factors is at best on the level of traditional risk factors, such as the size or value factors.

Finally, mispricing may present an anomaly itself capable of generating significant long-short return spreads, however this significance is also somewhat dubious, as while the SY-signal creates a significant and persistent over-performance of undervalued stocks up to 12 months subsequent to portfolio formation, the other measures of mispricing contradict this evidence. Namely, while the BG-signal does not create any significant difference, contradicting the evidence presented by [Bartram & Grinblatt \(2018\)](#), the Theil-Sen median creates a significant difference where overvalued stocks continue to outperform undervalued stocks for the subsequent 10 months, albeit this is mostly due to the post-2000 periods again and in fact the undervalued stocks earn the same or higher than the overvalued stocks prior to 2000.

7 Appendix

7.1 Appendix A: The construction of mispricing measures

7.1.1 Bartram and Grinblatt (2018) variables

While [Bartram & Grinblatt \(2018\)](#) describe their methodology of obtaining and constructing their accounting variables required for the mispricing measure construction, this section attempts to clarify this as well as any potential deviations, such as omitting two of the original independent variables. For the accounting variables used for explaining the market capitalization of a firm each month, the Quarterly Fundamentals of the CCM database is used.

For the 15 balance sheet items, the last released, non-missing value is taken for month t . These balance sheet items follow as:

- **ATQ:** total assets
- **LCOQ:** total other current liabilities
- **SEQQ:** total parent stockholders equity
- **ICAPTQ:** total invested capital
- **PSTKRQ:** preferred redeemable stock
- **PPENTQ:** total net property, plant and equipment
- **CEQQ:** total common/ordinary equity
- **PSTKQ:** total preferred stock
- **DLTTQ:** total long-term debt
- **AOQ:** total other assets
- **LTQ:** total liabilities
- **LOQ:** total other liabilities
- **CHEQ:** cash and short-term investments
- **ACOQ:** total other current assets
- **APQ:** accounts payable

For the 11 income statement items the methodology is slightly different. For these 11 variables, the obtained value for month t is the sum of the last four, non-missing and released quarterly information. While the quarters need not correspond with the exact quarters of a financial year, all quarterly values must be non-missing for the sum. These income statement and cash flow statement items follow as:

- **SALEQ:** net sales/turnover
- **IBQ:** income before extraordinary items
- **NIQ:** net income (loss)
- **XIDOQ:** extraordinary items and discontinued operations
- **IBADJQ:** income before extraordinary items, adjusted for common stock equivalents
- **IBCOMQ:** income before extraordinary items, available for common
- **PIQ:** pretax income
- **TXTQ:** total income taxes
- **NOPIQ:** non-operating income (loss)
- **DOQ:** discontinued operations
- **DVPQ:** preferred dividends

The release information is constructed as the following: the release date is set to be the final date (CCM variable `fdateq`) when the data is officially finalised and released.

In case this variable is not available, release date is set to be the one month lag of the quarterly earnings report date (CCM variable `rdq`). In case this variable is also unavailable, the release date is set to be the six months lag of the end date of the fiscal period the accounting information is from. This procedure is constructed in order to ensure using up-to-date data as much as possible, but root out potentially using private/insider information not yet available for the public.

Furthermore, while both the balance sheet and income statement variables point to the last released and available quarterly information, there is an upper limit to the past lag. For balance sheet items, in case such released information cannot be found in the past 24 months, the variable is set to missing. For income statement and cash flow items, all four quarters must be inside the 24-month period. If a company fails to report new information for 24 months, the variables are set to missing since the company might have gone bankrupt, bought up or involved in an M&A and not a separate entity anymore, or paused operations.

7.1.2 Stambaugh and Yuan (2017) variables

For the 11 variables employed by [Stambaugh & Yuan \(2017\)](#), the authors provide a detailed description of constructing these variables as well as citing the source of these methodologies. In this appendix section, I will describe the methodology I employed, which closely follows the authors' methodology with some deviation, where I explicitly label this deviation. The information release methodology slightly differs from [Stambaugh & Yuan \(2017\)](#), as the quarterly items follow the above-mentioned methodology previously described in Section 7.1.1. However, the annual item methodology follows the original, so that the latest annual data is used for calculating the anomaly characteristics so that the minimum time between the end of the fiscal period for the data and the portfolio formation period is 4 months. This means, that the stock holding month for constructing the mispricing factor must be at least 5 months after the end month of the fiscal period. The methodology of constructing the anomaly variables used for the mispricing signal of [Stambaugh & Yuan \(2017\)](#) follows as:

1. **Net Stock Issues:** Following [Fama & French \(2008\)](#), the authors describe the construction of the net stock issues variable as the log change between the adjusted shares outstanding of the previous fiscal year and the year before. The adjusted shares outstanding is calculated as the product of `CSHO` and `ADJEX_C` (CCM database). The previous fiscal year is considered to be the one ending at least 4 months before the portfolio formation period and consequently 5 months before the stock holding period.

$$SY1 = \log(CSHO * ADJEX_C)_y - \log(CSHO * ADJEX_C)_{y-1} \quad (9)$$

2. **Composite Equity Issues:** Following [Daniel & Titman \(2006\)](#), the authors describe the measure of composite equity issues to be the difference between the equity market capitalization growth and the cumulative stock return. The market capitalization is calculated as simply the product of the shares outstanding and the closing price of the month. The growth of the market capitalization is the log change from the beginning of the period to the end of the period. Furthermore, the calculated

measure is lagged by 4 months for consistency reasons of accounting information.

$$SY2 = L4.[(\log(PRC * SHROUT)_{t-1} - \log(PRC * SHROUT)_{t-12}) - (\log(PRC)_{t-1} - \log(PRC)_{t-12})] \quad (10)$$

3. **Accruals:** Following Sloan (1996), the authors construct the measure for accruals as the non-cash working capital minus depreciation and amortization (DP) scaled by the average of the last two available fiscal reports' total assets (AT). Furthermore, the non-cash working capital is constructed as the change in current assets (ACT) minus the change in cash and short-term investment (CHE) minus the change in current liabilities (LCT) plus the change in debt included in current liabilities (DLC) plus the change in income taxes payable (TXP).

$$SY3 = \frac{NWC_y - DP_y}{\frac{AT_y + AT_{y-1}}{2}} \quad (11)$$

where

$$NWC_y = (ACT_y - ACT_{y-1}) - (CHE_y - CHE_{y-1}) - (LCT_y - LCT_{y-1}) + (DLC_y - DLC_{y-1}) + (TXP_y - TXP_{y-1}) \quad (12)$$

4. **Net Operating Assets:** Following Hirshleifer et al. (2004), the authors construct the net operating assets as the difference of operating assets and operating liabilities scaled by the lagged total assets (AT). Furthermore, operating assets are constructed from total assets (AT) minus cash and short-term investments (CHE). Operating liabilities equal total assets (AT) minus debt included in current liabilities (DLC) minus long-term debt (DLTT), minus common equity (CEQ) minus minority interest (MIB) minus preferred stocks (PSTK). MIB and PSTK are set to 0 if their values are missing.

$$SY4 = \frac{OA_y - OL_y}{AT_{y-1}} \quad (13)$$

where

$$OA_y = AT_y - CHE_y \quad (14)$$

and

$$OL_y = AT_y - DLC_y - DLTT_y - CEQ_y - MIB_y - PSTK_y \quad (15)$$

5. **Asset Growth:** Following Cooper et al. (2008), the authors construct the asset growth variable as the log of the quotient of total assets (AT) from year $y - 1$ to y .

$$SY5 = \log\left(\frac{AT_y}{AT_{y-1}}\right) \quad (16)$$

6. **Investment to Assets:** Following Titman et al. (2004), the authors construct the investment to assets as the change in plant, property and equipment (PPEGT) plus the change in inventories (INVT), scaled by lagged total assets (AT).

$$SY6 = \frac{(PPEGT_y - PPEGT_{y-1}) + (INVT_y - INVT_{y-1})}{AT_{y-1}} \quad (17)$$

7. **Distress:** Following [Campbell et al. \(2008\)](#), the authors define the distress score as probability of failure (default) in a dynamic logit model. However, in my paper, there are some small deviations from the original methodology to avoid data issues. The probability of failure is estimated with the following equation:

$$\begin{aligned} SY7 = & -20.26 * NIMTAAVG + 1.42 * TLMTA - 7.13 * EXRETAVG \\ & + 1.41 * SIGMA - 0.045 * RSIZE - 2.13 * CASHMTA \\ & + 0.075 * MB - 0.058 * PRICE - 9.16 \end{aligned} \quad (18)$$

where

$$NIMTAAVG_{t-1,t-12} = \frac{1 - \phi^3}{1 - \phi^{12}} (NIMTA_{t-1,t-3} + \dots + \phi^9 * NIMTA_{t-10,t-12}) \quad (19)$$

$$EXRETAVG_{t-1,t-12} = \frac{1 - \phi}{1 - \phi^{12}} (EXRET_{t-1} + \dots + \phi^{11} * EXRET_{t-12}) \quad (20)$$

and

$$\phi = 2^{-1/3} \quad (21)$$

NIMTA is the net income (NIQ) scaled by the firm size, i.e. the sum of liabilities (LTQ) and market capitalization (the latter from CRSP). EXRET is the excess return of the stock, computed by the log return of the stock minus the log return of the S&P500 index. If a monthly/quarterly value is missing for NIMTA or EXRET for a given firm, it is instead replaced by the cross-sectional mean for that period (Any firm is included in these cross-sectional means only if all 4 of the inclusion rules have been satisfied for the period). TLMTA is the total liabilities (LTQ) scaled by the firm size (sum of LTQ and market cap). SIGMA is the stock return's daily standard deviation for the past 3 months (for month t , months $t-1$ to $t-3$ are used), annualized on the basis of average trading days on 10-year long intervals. This standard deviation is only calculated if a stock has at least 5 non-missing daily returns in the examined period. RSIZE is the log ratio of the stock's market capitalization and the S&P500 market capitalization. CASHMTA is the cash and short-term investments item (CHEQ) scaled by firm size (LTQ + market cap). MB is the market-to-book ratio, however, the adjustment suggested by [Campbell et al. \(2008\)](#) is not applied to avoid data issues, hence it is simply the market capitalization scaled by the book value of the company, where book value is the book-value-per-share multiplied by the outstanding shares. PRICE is the log of the most recent month's price, truncated at 15 as suggested by [Stambaugh & Yuan \(2017\)](#). However, all variables are winsorized at a 5% level, including PRICE as well to make the winsorizing more consistent and remove extreme outliers. Monthly variables are for the most recent month, while quarterly values are the most recent released quarterly data points in accordance with the release information construction described in Section 7.1.1.

8. **O-Score:** Following [Ohlson \(1980\)](#), the authors construct the main O-score measure from several different variables. The equation of the O-score gives a measure about default likelihood, which can be converted into default probability linearly

(the higher the O-score the higher the default probability). This equation of the O-score calculation follows as:

$$\begin{aligned} SY8 = & -0.407 * SIZE + 6.03 * TLTA - 1.43 * WCTA + 0.076 * CLCA \\ & - 1.72 * OENEG - 2.37 * NITA - 1.83 * FUTL + 0.285 * INTWO \\ & - 0.521 * CHIN - 1.32 \end{aligned} \quad (22)$$

where SIZE is the log of total assets (AT). TLTA is the book value of the company's debt (DLC and DLTT) scaled by total assets (AT). WCTA is the working capital (ACT - LCT) scaled by total assets (AT). CLCA is the current liabilities (LCT) scaled by current assets (ACT). OENEG is a dummy variable, which takes the value of 1 if total liabilities (LT) exceed total assets (AT) and the value of 0 in case liabilities do not exceed assets. NITA is the net income item (NI) scaled by total assets (AT). FUTL is funds provided by operations (PI) scaled by total liabilities (LT). INTWO is another binary variable set to 1 if net income (NI) is negative in the past two years and set to 0 otherwise. CHIN is the ratio of the net income difference ($NI_t - NI_{t-1}$) and the sum of the absolute values of net income for the same period ($|NI_t| + |NI_{t-1}|$).

9. **Momentum:** Following [Carhart \(1997\)](#), the authors define the momentum for ranking month t as the cumulative stock log returns from $t - 11$ through $t - 1$ months. This means, that the holding period month in the cross-sectional analysis is $t + 1$.

$$SY9 = \sum_{i=t-11}^{t-1} (\log(PRC)_i - \log(PRC)_{i-1}) \quad (23)$$

10. **Gross Profitability Premium:** Following [Novy-Marx \(2013\)](#), the authors define the gross profitability premium as the revenues (REVT) minus the costs of goods sold (COGS), scaled by the total assets (AT).

$$SY10 = \frac{REVT_y - COGS_y}{AT_y} \quad (24)$$

11. **Return on Assets:** Following [Chen et al. \(2011\)](#), the authors construct the return on assets as the income before extraordinary items (IBQ) scaled by the lagged total assets (AT), where both variables are from quarterly reports. For this variable, as for other quarterly variables previously described, my paper follows the methodology of using the most recent released quarterly data, where the release date is the same 3-step determination procedure as before.

$$SY11 = \frac{IBQ_q}{ATQ_{q-1}} \quad (25)$$

7.1.3 Bartram and Grinblatt variables with a simulation approach

An alternative way of obtaining the mispricing estimates from the cross-sectional regression of Equation (1) with the variables described in Section 7.1.1 is constructed utilising a simulation approach. [Bartram & Grinblatt \(2018\)](#) themselves describe that one major inadequacy of their cross-sectional fair value estimation procedure is that the estimation may result in rather inaccurate estimations in real life, albeit the peer-to-peer fair value

evaluation stays relevant. Inevitably, the fair value estimation may not be precise in consideration to the real life value in a cross-sectional regression with thousands of equities with different characteristics in the regression pool. Since the regression coefficients and thus the fair value estimation may be biased due to potential heteroskedasticity and non-normal distribution of regression variables, the Theil-Sen method is called for obtaining the median fair values by [Bartram & Grinblatt \(2018\)](#). As [Theil \(1950\)](#) describes, the confidence interval of the regression estimates can be reduced by a combinatoric procedure of observation points, thus making the estimates more robust to potential biases. Since the complete method of [Theil \(1950\)](#) is computationally unfeasible considering thousands of companies per month and that the large number of independent variables would require some minimum number of observations per regression, the incomplete method is utilised for estimating coefficients.

Hence, as [Bartram & Grinblatt \(2018\)](#) argue, the Theil-Sen median is obtained not by all pairwise (or group-wise) comparisons, but rather as a simulation with random sampling of regression pools. Each month, a random sample of 100 companies fit for the cross-sectional valuation estimation is drawn and the fair value estimated using the cross-sectional regression of Equation (1). This procedure is repeated 100,000 times every month to ensure a large number of fair value estimates in heterogeneous environment and subsequently, the median value of the fair value estimates is obtained. The mispricing signal from the fair value estimates is calculated the same way as described in Section 4.1.

7.2 Appendix B: Result outputs

Figure 6: Alpha patterns for Size anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

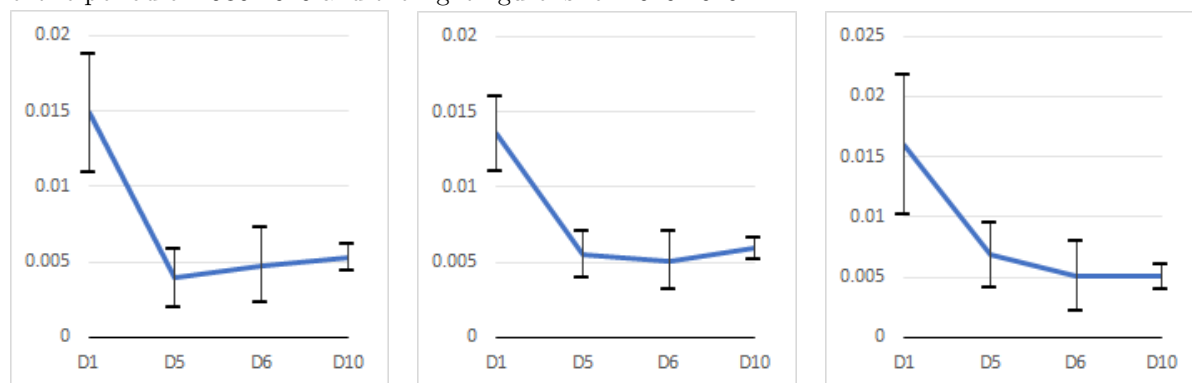


Figure 7: Alpha patterns for BM anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

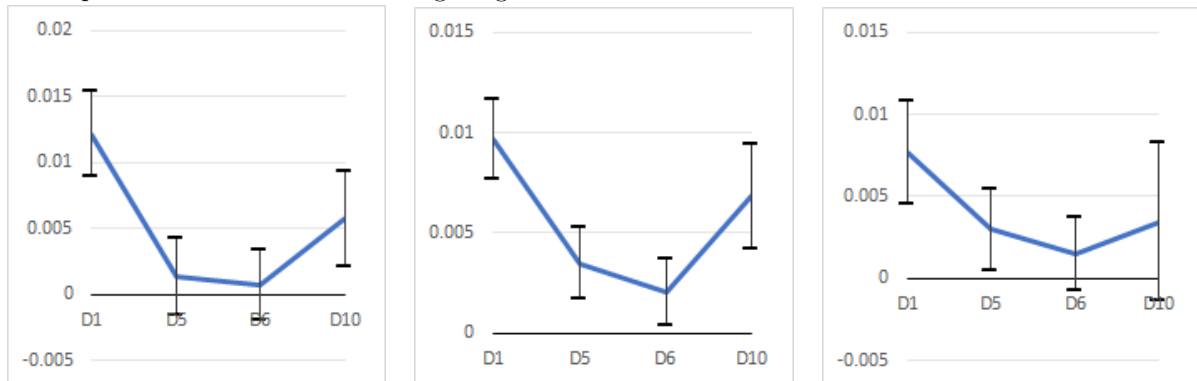


Figure 8: Alpha patterns for OP anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

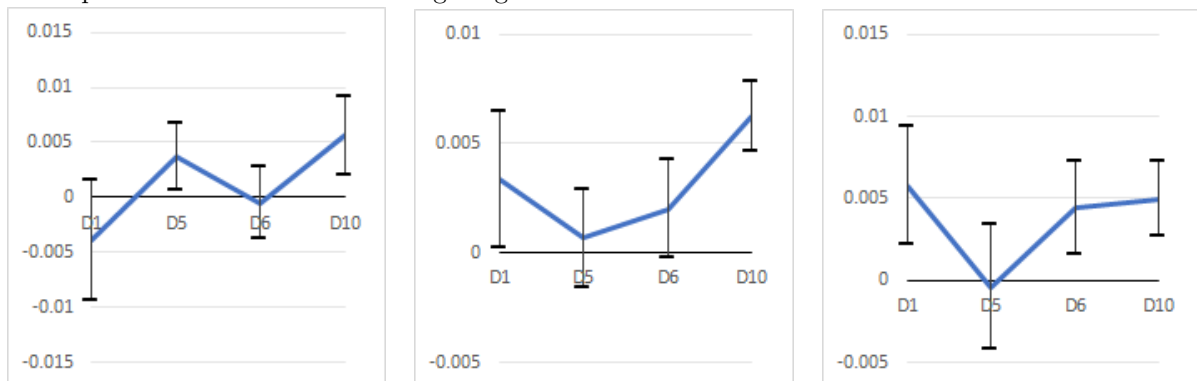


Figure 9: Alpha patterns for INV anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

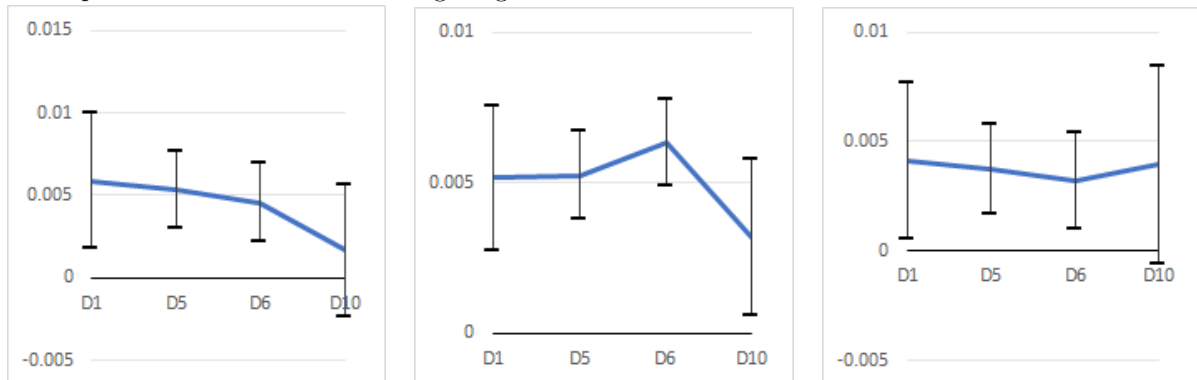


Figure 10: Alpha patterns for DP anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

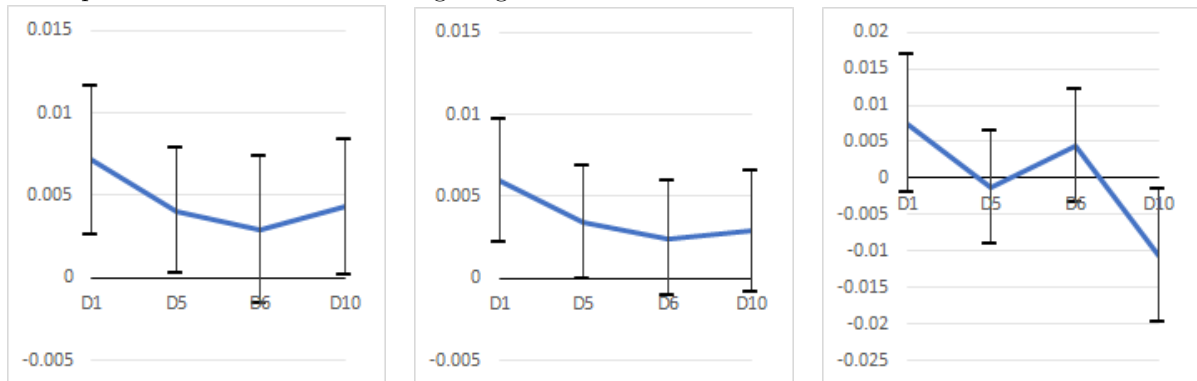


Figure 11: Alpha patterns for NETSTO anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

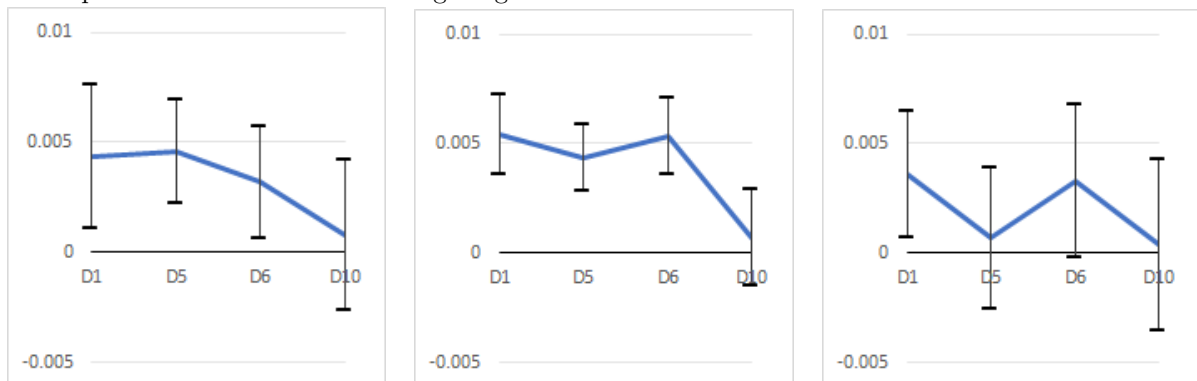


Figure 12: Alpha patterns for COMPEQ anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

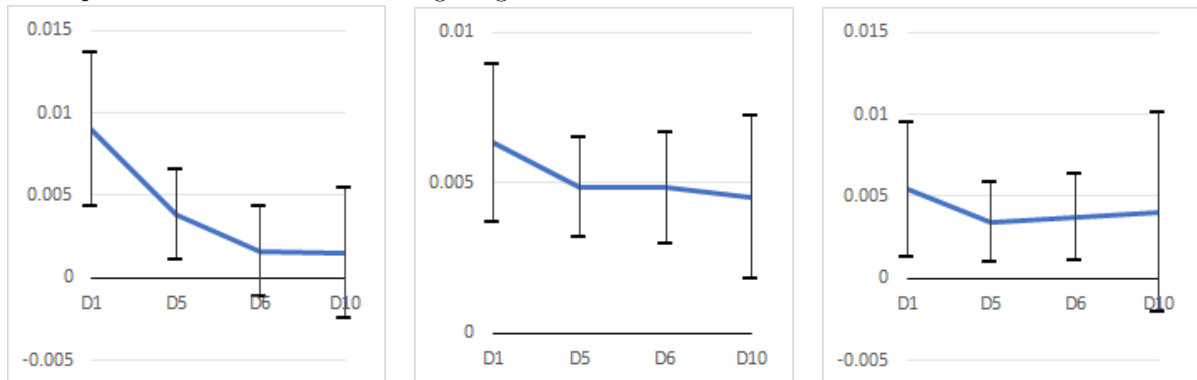


Figure 13: Alpha patterns for NETOPA anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

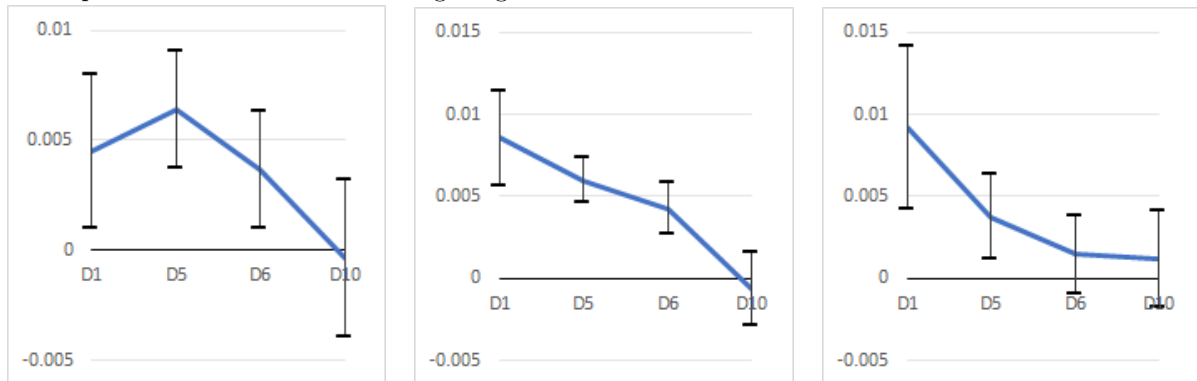


Figure 14: Alpha patterns for INVTOA anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

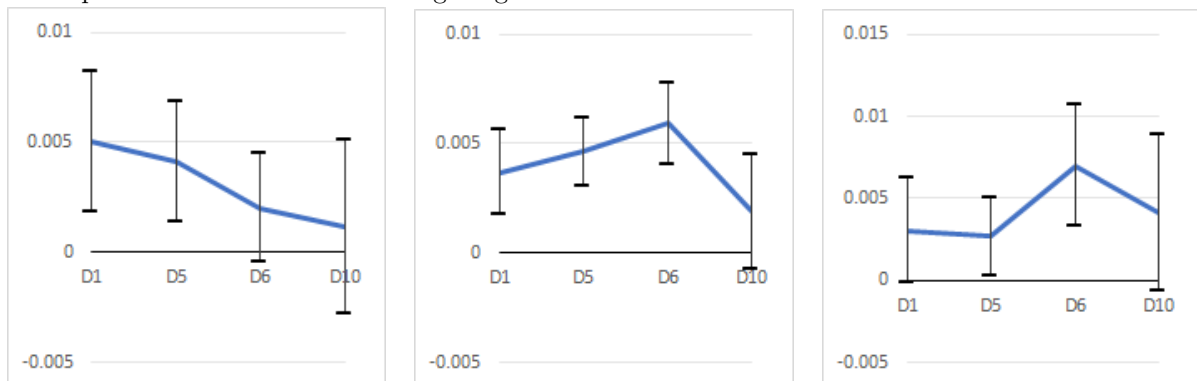


Figure 15: Alpha patterns for DISTRESS anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

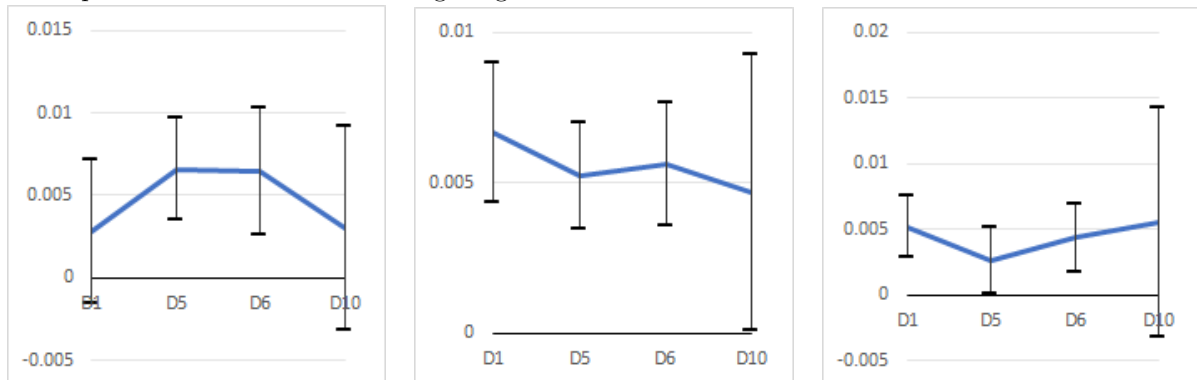


Figure 16: Alpha patterns for OSCORE anomaly estimated by FF3

The three sub-figures present the patterns in alphas with confidence intervals included from D1 through D10, where the left figure shows the pattern estimated for the 1980-89 period, the middle shows the entire period of 1980-2020 and the right figure is for 2010-2020

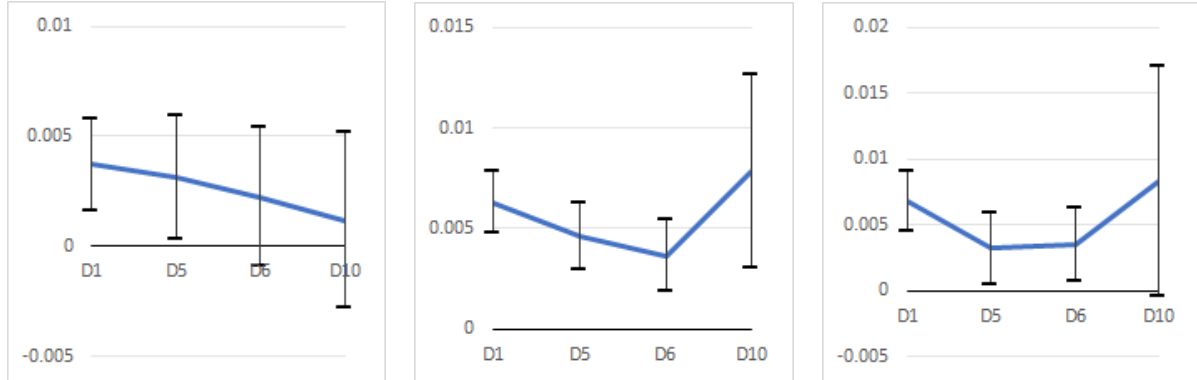


Table 8: Alpha coefficients for anomalies in the CAPM model

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1980-2020. The finite-sample GRS-test significance along with the estimated F-statistics in parentheses are provided in the last column.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10	GRS
Size	0.0194*** (9.84)	0.0248*** (12.51)	0.0229*** (10.44)	0.0246*** (6.92)	0.0198*** (9.13)	0.0179*** (9.26)	0.0160*** (8.67)	0.0139*** (8.66)	0.0113*** (8.54)	0.0095*** (9.00)	0.0054*** (12.82)	*** (29.83)
BM	-0.0068** (-2.67)	0.0092*** (6.72)	0.0049*** (5.17)	0.0046*** (5.35)	0.0047*** (6.38)	0.0057*** (6.34)	0.0054*** (6.08)	0.0060*** (6.44)	0.0079*** (7.78)	0.0110*** (8.04)	0.0161*** (8.90)	*** (23.39)
OP	0.0034 (1.61)	0.0095*** (4.95)	0.0075*** (4.03)	0.0055*** (3.92)	0.0064*** (5.17)	0.0048*** (3.93)	0.0048*** (4.26)	0.0041*** (4.64)	0.0058*** (6.55)	0.0071*** (8.91)	0.0062*** (7.83)	*** (18.86)
INV	0.0037* (2.08)	0.0095*** (7.13)	0.0087*** (8.82)	0.0074*** (10.18)	0.0054*** (7.54)	0.0059*** (8.31)	0.0061*** (8.85)	0.0061*** (7.71)	0.0069*** (5.56)	0.0075*** (5.88)	0.0058*** (3.87)	*** (31.25)
DP	0.0020 (0.80)	0.0068*** (3.80)	0.0052** (3.07)	0.0069*** (4.19)	0.0065*** (3.55)	0.0040* (2.38)	0.0027 (1.59)	0.0058*** (3.98)	0.0049** (3.08)	0.0040** (2.99)	0.0048** (2.73)	*** (6.23)
MOM	-0.0092* (-2.58)	0.0074** (3.05)	0.0051** (2.92)	0.0060*** (5.02)	0.0050*** (5.27)	0.0049** (6.72)	0.0042*** (5.30)	0.0062*** (7.80)	0.0064*** (6.24)	0.0086*** (5.52)	0.0166*** (6.83)	*** (20.21)
NETSTO	0.0032* (2.32)	0.0075*** (8.04)	0.0049*** (7.54)	0.0060*** (7.25)	0.0058*** (6.40)	0.0056*** (7.42)	0.0073*** (7.97)	0.0081*** (7.06)	0.0085*** (6.53)	0.0080*** (5.31)	0.0042*** (3.45)	*** (27.94)
COMPEQ	-0.0007 (-0.38)	0.0080*** (5.71)	0.0073*** (7.47)	0.0054*** (7.19)	0.0064*** (8.38)	0.0059*** (7.36)	0.0070*** (7.45)	0.0069*** (6.47)	0.0080*** (6.38)	0.0098*** (6.11)	0.0087*** (5.79)	*** (24.08)
ACCR	0.0010 (0.53)	0.0083*** (5.74)	0.0056*** (5.08)	0.0072*** (7.57)	0.0052*** (7.30)	0.0063*** (9.09)	0.0064*** (9.43)	0.0053*** (5.83)	0.0048*** (4.95)	0.0065*** (4.95)	0.0074*** (4.37)	*** (23.15)
NETOPA	0.0072*** (4.11)	0.0104*** (6.32)	0.0093*** (6.99)	0.0067*** (8.31)	0.0056*** (7.52)	0.0065*** (9.68)	0.0047*** (6.26)	0.0040*** (5.13)	0.0054*** (6.34)	0.0044*** (4.39)	0.0031** (2.61)	*** (29.69)
INVTOA	0.0030* (2.01)	0.0076*** (7.01)	0.0058*** (6.80)	0.0058*** (7.07)	0.0069*** (9.02)	0.0058*** (7.61)	0.0068*** (7.41)	0.0052*** (5.68)	0.0071*** (6.17)	0.0056*** (4.82)	0.0046*** (3.40)	*** (22.91)
DISTRESS	-0.0035 (-1.23)	0.0077*** (6.49)	0.0054*** (6.27)	0.0051*** (7.11)	0.0056*** (6.57)	0.0073*** (8.13)	0.0079*** (7.50)	0.0064*** (5.67)	0.0076*** (5.09)	0.0081*** (3.96)	0.0112*** (4.49)	*** (19.80)
OSCORE	-0.0127*** (-3.84)	0.0056*** (7.33)	0.0047*** (8.28)	0.0061*** (8.31)	0.0062*** (7.69)	0.0068*** (8.04)	0.0077*** (7.57)	0.0089*** (6.80)	0.0111*** (7.18)	0.0119*** (4.75)	0.0184*** (5.23)	*** (26.42)
RETONA	-0.0052* (-2.05)	0.0077*** (7.30)	0.0065*** (8.32)	0.0066*** (8.18)	0.0049*** (6.82)	0.0057*** (7.66)	0.0059*** (7.18)	0.0063*** (7.41)	0.0055*** (4.25)	0.0072*** (3.91)	0.0129*** (4.99)	*** (31.35)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Alpha coefficients for anomalies in the FF3 model

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1980-2020. The finite-sample GRS-test significance along with the estimated F-statistics in parentheses are provided in the last column.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10	GRS
Size	0.0076*** (5.96)	0.0135*** (10.67)	0.0091*** (8.29)	0.0117*** (4.65)	0.0059*** (6.76)	0.0055*** (6.96)	0.0051*** (5.18)	0.0048*** (5.03)	0.0045*** (5.04)	0.0048*** (5.64)	0.0059*** (15.79)	*** (44.01)
BM	0.0028 (1.62)	0.0096*** (9.47)	0.0055*** (6.72)	0.0037*** (4.47)	0.0030*** (4.10)	0.0035*** (3.86)	0.0021* (2.47)	0.0028** (3.23)	0.0039*** (4.69)	0.0050*** (4.58)	0.0068*** (5.12)	*** (17.83)
OP	-0.0029 (-1.53)	0.0034* (2.14)	0.0018 (1.09)	0.0004 (0.31)	0.0025* (2.11)	0.0007 (0.60)	0.0020 (1.78)	0.0024** (2.76)	0.0047*** (5.30)	0.0081*** (9.86)	0.0063*** (7.63)	*** (18.86)
INV	0.0020 (1.09)	0.0052*** (4.19)	0.0062*** (6.28)	0.0060*** (7.96)	0.0040*** (5.44)	0.0052*** (7.04)	0.0064*** (8.66)	0.0054*** (6.55)	0.0047*** (3.99)	0.0074*** (6.32)	0.0032* (2.40)	*** (24.38)
DP	0.0031 (1.18)	0.0060** (3.15)	0.0032 (1.86)	0.0055** (3.17)	0.0048* (2.54)	0.0034 (1.94)	0.0024 (1.37)	0.0053*** (3.44)	0.0039* (2.32)	0.0038** (2.71)	0.0029 (1.54)	*** (3.92)
MOM	-0.0159*** (-5.02)	-0.0022 (-0.98)	-0.0010 (-0.63)	0.0027* (2.28)	0.0027** (2.86)	0.0037*** (4.90)	0.0037*** (4.38)	0.0058*** (7.03)	0.0065*** (6.42)	0.0072*** (5.34)	0.0137*** (6.92)	*** (15.71)
NETSTO	0.0047** (3.21)	0.0054*** (5.87)	0.0047*** (6.82)	0.0058*** (6.56)	0.0049*** (5.09)	0.0044*** (5.66)	0.0053*** (5.89)	0.0070*** (6.30)	0.0063*** (5.00)	0.0047*** (3.42)	0.0007 (0.65)	*** (21.27)
COMPEQ	0.0018 (0.99)	0.0063*** (4.75)	0.0072*** (7.29)	0.0056*** (6.98)	0.0058*** (7.29)	0.0048*** (5.74)	0.0048*** (5.18)	0.0042*** (3.96)	0.0047*** (3.94)	0.0050*** (3.42)	0.0045** (3.29)	*** (20.26)
ACCR	0.0044* (2.34)	0.0064*** (4.44)	0.0045*** (3.90)	0.0061*** (6.34)	0.0042*** (5.60)	0.0057*** (7.91)	0.0059*** (8.56)	0.0040*** (4.29)	0.0028** (2.95)	0.0027* (2.31)	0.0020 (1.33)	*** (20.20)
NETOPA	0.0092*** (5.23)	0.0086*** (5.81)	0.0077*** (6.24)	0.0059*** (7.30)	0.0050*** (6.46)	0.0060*** (8.41)	0.0042*** (5.31)	0.0025** (3.06)	0.0035*** (4.10)	0.0014 (1.56)	-0.0007 (-0.58)	*** (24.45)
INVTOA	0.0018 (1.15)	0.0037*** (3.74)	0.0038*** (4.42)	0.0049*** (5.74)	0.0067*** (8.39)	0.0046*** (5.93)	0.0059*** (6.29)	0.0041*** (4.45)	0.0063*** (5.63)	0.0035** (3.15)	0.0019 (1.40)	*** (18.84)
DISTRESS	0.0020 (0.70)	0.0067*** (5.62)	0.0047*** (5.30)	0.0048*** (6.35)	0.0043*** (4.98)	0.0052*** (5.82)	0.0056*** (5.41)	0.0037*** (3.43)	0.0036** (2.65)	0.0025 (1.30)	0.0047* (2.00)	*** (15.42)
OSCORE	-0.0015 (-0.65)	0.0063*** (8.23)	0.0047*** (7.94)	0.0048*** (6.45)	0.0041*** (5.05)	0.0046*** (5.46)	0.0037*** (4.03)	0.0041*** (3.64)	0.0052*** (4.30)	0.0039* (2.16)	0.0078** (3.22)	*** (21.81)
RETONA	0.0031 (1.34)	0.0082*** (8.36)	0.0063*** (8.47)	0.0060*** (7.16)	0.0035*** (4.77)	0.0041*** (5.42)	0.0043*** (5.06)	0.0041*** (4.80)	0.0009 (0.79)	0.0013 (0.83)	0.0052* (2.48)	*** (25.97)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Alpha coefficients for anomalies in the FF5 model

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1980-2020. The finite-sample GRS-test significance along with the estimated F-statistics in parentheses are provided in the last column.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10	GRS
Size	0.0073*** (5.67)	0.0136*** (10.61)	0.0097*** (8.88)	0.0098*** (3.96)	0.0074*** (9.52)	0.0069*** (9.88)	0.0065*** (7.04)	0.0061*** (6.79)	0.0057*** (6.65)	0.0059*** (7.55)	0.0063*** (17.28)	*** (51.58)
BM	0.0024 (1.36)	0.0101*** (9.84)	0.0060*** (7.45)	0.0041*** (4.94)	0.0033*** (4.44)	0.0039*** (4.26)	0.0022** (2.59)	0.0026** (3.01)	0.0041*** (4.92)	0.0061*** (5.69)	0.0077*** (5.74)	*** (21.71)
OP	0.0014 (1.08)	0.0068*** (5.70)	0.0052*** (4.34)	0.0026* (2.47)	0.0038*** (3.47)	0.0016 (1.43)	0.0040*** (3.90)	0.0028** (3.16)	0.0052*** (5.77)	0.0081*** (10.23)	0.0054*** (7.00)	*** (21.60)
INV	-0.0014 (-1.07)	0.0045*** (4.07)	0.0055*** (6.09)	0.0052*** (7.39)	0.0034*** (4.94)	0.0046*** (6.32)	0.0060*** (8.13)	0.0057*** (6.87)	0.0064*** (6.07)	0.0097*** (10.24)	0.0059*** (5.68)	*** (25.61)
DP	0.0018 (0.69)	0.0049* (2.57)	0.0032 (1.81)	0.0056** (3.17)	0.0051** (2.61)	0.0030 (1.69)	0.0025 (1.39)	0.0049** (3.11)	0.0035* (2.07)	0.0039** (2.73)	0.0031 (1.65)	*** (3.44)
MOM	-0.0140*** (-4.44)	0.0013 (0.63)	0.0008 (0.48)	0.0034** (2.87)	0.0031** (3.29)	0.0036*** (4.81)	0.0031*** (3.69)	0.0054*** (6.50)	0.0062*** (6.01)	0.0075*** (5.56)	0.0152*** (7.79)	*** (17.56)
NETSTO	0.0031* (2.20)	0.0054*** (5.74)	0.0040*** (6.01)	0.0049*** (5.77)	0.0042*** (4.43)	0.0044*** (5.64)	0.0060*** (6.61)	0.0084*** (8.04)	0.0086*** (7.62)	0.0070*** (5.51)	0.0022* (2.12)	*** (21.34)
COMPEQ	0.0021 (1.13)	0.0076*** (5.90)	0.0070*** (7.12)	0.0056*** (6.79)	0.0061*** (7.54)	0.0045*** (5.33)	0.0051*** (5.41)	0.0052*** (5.03)	0.0061*** (5.39)	0.0071*** (5.27)	0.0055*** (4.04)	*** (23.46)
ACCR	0.0036 (1.93)	0.0081*** (5.86)	0.0056*** (5.17)	0.0068*** (7.07)	0.0045*** (6.08)	0.0057*** (7.82)	0.0055*** (7.97)	0.0040*** (4.26)	0.0036*** (3.92)	0.0039*** (3.45)	0.0046*** (3.61)	*** (22.36)
NETOPA	0.0097*** (5.54)	0.0109*** (8.06)	0.0086*** (7.28)	0.0064*** (7.93)	0.0043*** (5.61)	0.0058*** (8.08)	0.0040*** (4.94)	0.0028*** (3.46)	0.0045*** (5.45)	0.0020* (2.16)	0.0012 (1.26)	*** (26.67)
INVTOA	0.0008 (0.55)	0.0037*** (3.92)	0.0030*** (3.62)	0.0053*** (6.28)	0.0063*** (7.83)	0.0044*** (5.66)	0.0062*** (6.47)	0.0055*** (6.49)	0.0078*** (7.33)	0.0050*** (4.94)	0.0030* (2.33)	*** (21.84)
DISTRESS	-0.0006 (-0.21)	0.0066*** (5.47)	0.0042*** (4.79)	0.0045*** (5.97)	0.0044*** (5.06)	0.0057*** (6.32)	0.0068*** (6.90)	0.0047*** (4.43)	0.0053*** (4.25)	0.0050** (2.84)	0.0072** (3.22)	*** (18.13)
OSCORE	-0.0043* (-2.20)	0.0073*** (10.31)	0.0048*** (7.96)	0.0052*** (6.91)	0.0041*** (5.04)	0.0046*** (5.36)	0.0039*** (4.35)	0.0047*** (4.25)	0.0058*** (4.96)	0.0073*** (4.95)	0.0117*** (5.73)	*** (25.75)
RETONA	-0.0004 (-0.19)	0.0089*** (9.63)	0.0068*** (9.18)	0.0060*** (7.14)	0.0034*** (4.55)	0.0040*** (5.28)	0.0040*** (4.78)	0.0042*** (4.83)	0.0021* (2.00)	0.0043*** (3.51)	0.0093*** (5.68)	*** (30.71)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Mispricing and alpha coefficients for Size anomaly in augmented factor models
The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	-0.1709** (-3.07)	-0.3106*** (-5.68)	-0.4182*** (-7.02)	-0.3497*** (-3.48)	-0.4545*** (-7.81)	-0.3766*** (-7.18)	-0.3478*** (-6.93)	-0.2808*** (-6.38)	-0.2376*** (-6.55)	-0.1395*** (-4.74)	-0.1397*** (-13.81)
CAPM+BG α	0.0194*** (9.91)	0.0247*** (12.86)	0.0228*** (10.89)	0.0246*** (6.98)	0.0197*** (9.63)	0.0178*** (9.68)	0.0159*** (9.03)	0.0138*** (8.96)	0.0113*** (8.86)	0.0095*** (9.16)	0.0053*** (15.01)
FF3+BG	-0.0566 (-1.17)	-0.1398** (-2.93)	-0.2505*** (-6.23)	1.0043*** (12.02)	-0.2149*** (-6.75)	-0.1419*** (-4.81)	-0.1124** (-3.03)	-0.0771* (-2.13)	-0.0681* (-1.99)	-0.0197 (-0.61)	-0.0833*** (-6.07)
FF3+BG α	0.0072*** (5.90)	0.0133*** (10.60)	0.0088*** (8.31)	0.0129*** (5.85)	0.0057*** (6.73)	0.0054*** (6.88)	0.0050*** (5.07)	0.0047*** (4.95)	0.0045*** (4.95)	0.0047*** (5.61)	0.0058*** (16.06)
FF5+BG	-0.0609 (-1.21)	-0.1328** (-2.66)	-0.2072*** (-4.98)	0.9697*** (11.20)	-0.1568*** (-5.28)	-0.0872** (-3.20)	-0.0481 (-1.33)	-0.0272 (-0.77)	-0.0065 (-0.19)	0.0492 (1.61)	-0.0719*** (-5.16)
FF5+BG α	0.0072*** (5.58)	0.0134*** (10.46)	0.0093*** (8.72)	0.0115*** (5.21)	0.0071*** (9.38)	0.0068*** (9.73)	0.0064*** (6.93)	0.0061*** (6.71)	0.0057*** (6.62)	0.0060*** (7.66)	0.0062*** (17.32)
CAPM+SY	-0.5039*** (-8.71)	-0.5221*** (-9.03)	-0.6370*** (-10.13)	-0.8310*** (-7.85)	-0.7255*** (-12.11)	-0.6145*** (-11.32)	-0.5432*** (-10.31)	-0.4438*** (-9.55)	-0.3661*** (-9.52)	-0.3076*** (-10.17)	-0.0182 (-1.38)
CAPM+SY α	0.0221*** (11.89)	0.0276*** (14.83)	0.0263*** (13.02)	0.0292*** (8.56)	0.0237*** (12.31)	0.0212*** (12.16)	0.0189*** (11.16)	0.0163*** (10.91)	0.0133*** (10.77)	0.0112*** (11.48)	0.0055*** (12.88)
FF3+SY	-0.0332 (-0.79)	-0.0591 (-1.42)	-0.0717* (-1.98)	-0.2147** (-2.61)	-0.1633*** (-5.83)	-0.1053*** (-4.08)	-0.0914** (-2.83)	-0.0642* (-2.04)	-0.0850** (-2.88)	-0.1265*** (-4.65)	-0.0259* (-2.10)
FF3+SY α	0.0079*** (5.90)	0.0141*** (10.57)	0.0099*** (8.51)	0.0139*** (5.27)	0.0076*** (8.48)	0.0066*** (8.00)	0.0060*** (5.84)	0.0055*** (5.44)	0.0054*** (5.73)	0.0060*** (6.95)	0.0062*** (15.69)
FF5+SY	-0.1133* (-2.10)	-0.0812 (-1.51)	-0.0307 (-0.67)	-0.7061*** (-7.14)	0.0218 (0.67)	0.1033*** (3.55)	0.1144** (2.99)	0.1529*** (4.11)	0.0755* (2.12)	0.0111 (0.34)	0.0321* (2.11)
FF5+SY α	0.0081*** (6.06)	0.0142*** (10.61)	0.0099*** (8.70)	0.0148*** (6.01)	0.0073*** (8.93)	0.0062*** (8.58)	0.0057*** (5.95)	0.0050*** (5.45)	0.0051*** (5.80)	0.0058*** (7.14)	0.0061*** (16.03)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Mispricing and alpha coefficients for BM anomaly in augmented factor models
The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	-0.9683*** (-16.55)	-0.5627*** (-18.89)	-0.3155*** (-13.55)	-0.1493*** (-6.36)	-0.0026 (-0.12)	0.0026 (0.10)	0.0505* (1.98)	0.1468*** (5.65)	0.2186*** (8.00)	0.3406*** (9.45)	0.4057*** (8.43)
CAPM+BG α	-0.0071*** (-3.44)	0.0091*** (8.71)	0.0049*** (5.96)	0.0045*** (5.52)	0.0047*** (6.38)	0.0057*** (6.34)	0.0055*** (6.11)	0.0061*** (6.68)	0.0080*** (8.32)	0.0111*** (8.80)	0.0162*** (9.57)
FF3+BG	-0.4297*** (-6.85)	-0.2486*** (-6.72)	-0.1241*** (-4.05)	0.0061 (0.20)	0.0654* (2.34)	0.0472 (1.38)	0.0455 (1.43)	0.0720* (2.18)	0.0185 (0.59)	0.1573*** (3.85)	0.1811*** (3.62)
FF3+BG α	0.0023 (1.37)	0.0093*** (9.57)	0.0054*** (6.62)	0.0037*** (4.47)	0.0031*** (4.22)	0.0036*** (3.93)	0.0021* (2.54)	0.0029*** (3.34)	0.0039*** (4.71)	0.0052*** (4.82)	0.0071*** (5.35)
FF5+BG	-0.5238*** (-8.16)	-0.2901*** (-7.67)	-0.1459*** (-4.69)	-0.0007 (-0.02)	0.0752* (2.58)	0.0749* (2.10)	0.0645 (1.94)	0.1050** (3.08)	0.0405 (1.23)	0.2022*** (4.94)	0.2338*** (4.55)
FF5+BG α	0.0014 (0.87)	0.0095*** (9.85)	0.0058*** (7.26)	0.0041*** (4.92)	0.0035*** (4.64)	0.0040*** (4.41)	0.0023** (2.73)	0.0028** (3.25)	0.0042*** (5.00)	0.0065*** (6.16)	0.0081*** (6.16)
CAPM+SY	0.5263*** (6.82)	-0.0173 (-0.40)	-0.0157 (-0.52)	-0.0936*** (-3.51)	-0.1013*** (-4.47)	-0.1068*** (-3.83)	-0.1427*** (-5.19)	-0.1395*** (-4.82)	-0.1954*** (-6.32)	-0.4072*** (-10.37)	-0.5437*** (-10.58)
CAPM+SY α	-0.0097*** (-3.91)	0.0093*** (6.69)	0.0050*** (5.18)	0.0051*** (5.92)	0.0052*** (7.17)	0.0063*** (6.99)	0.0062*** (7.03)	0.0068*** (7.31)	0.0090*** (9.04)	0.0133*** (10.50)	0.0190*** (11.51)
FF3+SY	0.3749*** (6.87)	0.0627 (1.87)	0.0141 (0.52)	-0.0368 (-1.36)	-0.0393 (-1.61)	-0.0236 (-0.79)	-0.0245 (-0.88)	-0.0474 (-1.64)	-0.1016*** (-3.76)	-0.2807*** (-8.31)	-0.3122*** (-7.47)
FF3+SY α	-0.0010 (-0.59)	0.0090*** (8.40)	0.0054*** (6.19)	0.0040*** (4.68)	0.0034*** (4.40)	0.0037*** (3.91)	0.0023** (2.63)	0.0033*** (3.59)	0.0049*** (5.71)	0.0079*** (7.29)	0.0100*** (7.50)
FF5+SY	0.5504*** (7.99)	0.1993*** (4.76)	0.1451*** (4.34)	0.0274 (0.80)	-0.0040 (-0.13)	0.0362 (0.95)	-0.0187 (-0.52)	-0.1299*** (-3.57)	-0.1264*** (-3.64)	-0.2420*** (-5.57)	-0.3512*** (-6.53)
FF5+SY α	-0.0015 (-0.88)	0.0086*** (8.30)	0.0050*** (6.04)	0.0039*** (4.51)	0.0033*** (4.29)	0.0036*** (3.82)	0.0023** (2.63)	0.0036*** (3.94)	0.0050*** (5.81)	0.0078*** (7.20)	0.0102*** (7.59)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Mispricing and alpha coefficients for OP anomaly in augmented factor models
The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	-0.4417*** (-7.85)	-0.5142*** (-10.31)	-0.4303*** (-8.63)	-0.1742*** (-4.41)	-0.1027** (-2.94)	-0.1316*** (-3.81)	-0.0289 (-0.89)	-0.1221*** (-4.97)	-0.1246*** (-5.10)	-0.0798*** (-3.56)	-0.0725** (-3.26)
CAPM+BG α	0.0033 (1.66)	0.0094*** (5.39)	0.0075*** (4.26)	0.0055*** (3.96)	0.0064*** (5.19)	0.0048*** (3.96)	0.0048*** (4.25)	0.0041*** (4.72)	0.0057*** (6.68)	0.0071*** (8.99)	0.0062*** (7.88)
FF3+BG	-0.2643*** (-3.74)	-0.2619*** (-4.45)	-0.2391*** (-3.90)	-0.1132* (-2.33)	-0.0042 (-0.09)	-0.0267 (-0.62)	0.0502 (1.17)	-0.0515 (-1.55)	-0.0591 (-1.75)	-0.0155 (-0.50)	0.0023 (0.08)
FF3+BG α	-0.0032 (-1.72)	0.0031* (1.97)	0.0015 (0.92)	0.0003 (0.20)	0.0025* (2.10)	0.0006 (0.57)	0.0021 (1.83)	0.0024** (2.69)	0.0047*** (5.22)	0.0081*** (9.82)	0.0063*** (7.62)
FF5+BG	0.0223 (0.43)	-0.0536 (-1.15)	0.0116 (0.25)	0.0567 (1.36)	0.0851* (1.97)	0.0207 (0.47)	0.1287** (3.26)	-0.0524 (-1.52)	-0.0631 (-1.80)	-0.0775* (-2.50)	-0.0760* (-2.53)
FF5+BG α	0.0015 (1.10)	0.0067*** (5.61)	0.0052*** (4.34)	0.0027* (2.57)	0.0040*** (3.61)	0.0016 (1.46)	0.0042*** (4.16)	0.0027** (3.05)	0.0051*** (5.64)	0.0080*** (10.08)	0.0053*** (6.84)
CAPM+SY	-0.7041*** (-12.17)	-0.5903*** (-10.79)	-0.5898*** (-11.16)	-0.3507*** (-8.42)	-0.3308*** (-9.21)	-0.2874*** (-7.87)	-0.3271*** (-10.05)	-0.0897** (-3.25)	-0.0428 (-1.55)	0.0249 (0.99)	0.1139*** (4.68)
CAPM+SY α	0.0072*** (3.87)	0.0128*** (7.25)	0.0108*** (6.33)	0.0074*** (5.56)	0.0082*** (7.08)	0.0064*** (5.44)	0.0066*** (6.31)	0.0046*** (5.17)	0.0060*** (6.73)	0.0070*** (8.61)	0.0055*** (7.09)
FF3+SY	-0.5028*** (-8.67)	-0.3488*** (-7.00)	-0.3843*** (-7.49)	-0.1641*** (-3.92)	-0.2006*** (-5.37)	-0.1319*** (-3.58)	-0.2594*** (-7.31)	-0.0089 (-0.31)	0.0178 (0.61)	0.0005 (0.02)	0.1540*** (5.88)
FF3+SY α	0.0023 (1.22)	0.0069*** (4.36)	0.0057*** (3.48)	0.0021 (1.55)	0.0045*** (3.77)	0.0020 (1.72)	0.0047*** (4.11)	0.0025** (2.71)	0.0045*** (4.82)	0.0081*** (9.33)	0.0047*** (5.59)
FF5+SY	-0.0293 (-0.53)	0.0708 (1.42)	-0.0114 (-0.23)	0.1361** (3.08)	-0.0722 (-1.56)	-0.0396 (-0.85)	-0.0366 (-0.86)	0.0650 (1.76)	0.1258*** (3.38)	0.0332 (1.00)	0.1002** (3.13)
FF5+SY α	0.0016 (1.18)	0.0063*** (5.07)	0.0053*** (4.22)	0.0017 (1.52)	0.0043*** (3.77)	0.0019 (1.61)	0.0042*** (3.98)	0.0023* (2.54)	0.0043*** (4.63)	0.0079*** (9.53)	0.0047*** (5.88)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Mispricing and alpha coefficients for INV anomaly in augmented factor models
The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	0.1694*** (3.41)	-0.2277*** (-6.24)	0.0454 (1.63)	0.0524* (1.72)	-0.0349 (-1.72)	0.0700*** (3.50)	-0.0731*** (-3.74)	-0.0613** (-2.75)	-0.2482*** (-7.38)	-0.3326*** (-9.95)	-0.3971*** (-10.24)
CAPM+BG α	0.0037* (2.13)	0.0094*** (7.36)	0.0087*** (8.84)	0.0074*** (10.25)	0.0054*** (7.54)	0.0059*** (8.43)	0.0061*** (8.94)	0.0061*** (7.75)	0.0069*** (5.81)	0.0075*** (6.38)	0.0057*** (4.19)
FF3+BG	-0.0330 (-0.48)	-0.1870*** (-4.07)	0.0146 (0.39)	0.0345 (1.22)	-0.0798** (-2.88)	0.0484 (1.72)	-0.0732** (-2.65)	-0.0128 (-0.41)	-0.0708 (-1.60)	-0.0852 (-1.92)	-0.1540** (-3.08)
FF3+BG α	0.0019 (1.06)	0.0049*** (4.06)	0.0063*** (6.29)	0.0060*** (8.01)	0.0039*** (5.33)	0.0053*** (7.13)	0.0063*** (8.58)	0.0054*** (6.52)	0.0046*** (3.92)	0.0073*** (6.24)	0.0030* (2.27)
FF5+BG	0.0860 (1.71)	-0.0953* (-2.19)	0.0884* (2.50)	0.0622* (2.27)	-0.0514 (-1.89)	0.0535 (1.87)	-0.0948** (-3.31)	-0.0230 (-0.71)	-0.0834* (-2.02)	-0.1166** (-3.18)	-0.1813*** (-4.53)
FF5+BG α	-0.0012 (-0.94)	0.0044*** (3.92)	0.0057*** (6.28)	0.0053*** (7.57)	0.0033*** (4.81)	0.0047*** (6.46)	0.0058*** (7.96)	0.0056*** (6.80)	0.0063*** (5.93)	0.0095*** (10.09)	0.0056*** (5.45)
CAPM+SY	0.4019*** (7.64)	-0.0943* (-2.26)	-0.0181 (-0.58)	0.0258 (1.12)	0.0454* (2.03)	0.0688** (3.10)	0.0560* (2.57)	-0.0506* (-2.04)	-0.2488*** (-6.62)	-0.2201*** (-5.60)	-0.4962*** (-11.93)
CAPM+SY α	0.0015 (0.87)	0.0100*** (7.44)	0.0088*** (8.78)	0.0073*** (9.84)	0.0051*** (7.11)	0.0055*** (7.74)	0.0058*** (8.34)	0.0063*** (7.97)	0.0083*** (6.84)	0.0087*** (6.92)	0.0085*** (6.35)
FF3+SY	0.5323*** (9.70)	0.1181** (2.93)	0.0825* (2.53)	0.0926*** (3.80)	0.1194*** (5.04)	0.1052*** (4.36)	0.0681** (2.83)	-0.0168 (-0.62)	-0.1513*** (-3.99)	-0.1976*** (-5.23)	-0.4142*** (-10.45)
FF3+SY α	-0.0035* (-1.98)	0.0039** (3.07)	0.0054*** (5.18)	0.0050*** (6.43)	0.0028*** (3.67)	0.0042*** (5.40)	0.0057*** (7.36)	0.0055*** (6.40)	0.0062*** (5.12)	0.0094*** (7.82)	0.0074*** (5.85)
FF5+SY	0.1032 (1.92)	0.0165 (0.35)	-0.0508 (-1.34)	-0.0203 (-0.69)	0.0618* (2.12)	0.0427 (1.39)	0.0442 (1.43)	0.0412 (1.19)	0.1309** (2.99)	0.1701*** (4.38)	-0.0867* (-1.99)
FF5+SY α	-0.0021 (-1.57)	0.0044*** (3.80)	0.0059*** (6.22)	0.0053*** (7.28)	0.0030*** (4.15)	0.0043*** (5.68)	0.0057*** (7.40)	0.0054*** (6.25)	0.0055*** (5.02)	0.0085*** (8.76)	0.0065*** (6.02)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Mispricing and alpha coefficients for DP anomaly in augmented factor models
The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	-0.0798 (-1.13)	-0.0588 (-1.15)	-0.2166*** (-4.54)	-0.1491** (-3.20)	-0.2181*** (-4.23)	-0.1334** (-2.81)	-0.1020* (-2.12)	0.0413 (0.99)	-0.0787 (-1.74)	0.0507 (1.34)	0.0210 (0.41)
CAPM+BG α	0.0020 (0.79)	0.0068*** (3.79)	0.0052** (3.10)	0.0069*** (4.21)	0.0065*** (3.58)	0.0040* (2.38)	0.0027 (1.58)	0.0058*** (3.98)	0.0049** (3.08)	0.0040** (3.00)	0.0048** (2.73)
FF3+BG	-0.0568 (-0.57)	-0.0492 (-0.68)	-0.0422 (-0.64)	-0.1363* (-2.08)	-0.1534* (-2.13)	-0.0146 (-0.22)	-0.0333 (-0.49)	0.1918** (3.30)	-0.1700** (-2.68)	0.0184 (0.34)	0.0077 (0.11)
FF3+BG α	0.0030 (1.15)	0.0059** (3.11)	0.0032 (1.82)	0.0053** (3.08)	0.0047* (2.45)	0.0034 (1.92)	0.0024 (1.34)	0.0056*** (3.63)	0.0037* (2.20)	0.0038** (2.72)	0.0029 (1.54)
FF5+BG	-0.1630 (-1.58)	-0.0787 (-1.05)	-0.0203 (-0.30)	-0.1565* (-2.28)	-0.1551* (-2.05)	-0.0207 (-0.30)	-0.0273 (-0.38)	0.1656** (2.73)	-0.1662* (-2.50)	0.0301 (0.54)	0.0843 (1.15)
FF5+BG α	0.0015 (0.58)	0.0048* (2.49)	0.0031 (1.78)	0.0053** (3.01)	0.0048* (2.47)	0.0030 (1.66)	0.0025 (1.36)	0.0052*** (3.32)	0.0032 (1.90)	0.0040** (2.75)	0.0032 (1.73)
CAPM+SY	0.3159*** (4.10)	-0.0017 (-0.03)	-0.0422 (-0.78)	-0.0072 (-0.14)	-0.0360 (-0.62)	-0.0021 (-0.04)	-0.0758 (-1.42)	-0.0025 (-0.05)	0.1539** (3.10)	0.0238 (0.57)	-0.3175*** (-5.88)
CAPM+SY α	0.0003 (0.10)	0.0068*** (3.74)	0.0055** (3.16)	0.0070*** (4.15)	0.0067*** (3.60)	0.0040* (2.35)	0.0031 (1.81)	0.0058*** (3.92)	0.0040* (2.54)	0.0038** (2.85)	0.0066*** (3.77)
FF3+SY	0.3488*** (4.08)	0.0443 (0.71)	0.0900 (1.59)	0.0771 (1.35)	0.0677 (1.08)	0.0550 (0.95)	-0.0621 (-1.05)	0.0324 (0.64)	0.2351*** (4.31)	0.0265 (0.57)	-0.3045*** (-5.07)
FF3+SY α	-0.0005 (-0.16)	0.0055** (2.76)	0.0023 (1.26)	0.0047* (2.58)	0.0042* (2.06)	0.0028 (1.53)	0.0031 (1.63)	0.0050** (3.06)	0.0015 (0.86)	0.0035* (2.38)	0.0060** (3.11)
FF5+SY	0.3398** (3.09)	-0.1503 (-1.88)	0.1292 (1.77)	0.1486* (2.02)	0.1535 (1.89)	0.0084 (0.11)	-0.0873 (-1.15)	-0.0283 (-0.43)	0.3005*** (4.28)	0.0580 (0.97)	-0.4901*** (-6.50)
FF5+SY α	-0.0006 (-0.21)	0.0060** (3.01)	0.0022 (1.24)	0.0045* (2.48)	0.0040* (1.97)	0.0029 (1.59)	0.0031 (1.66)	0.0051** (3.11)	0.0014 (0.81)	0.0035* (2.34)	0.0066*** (3.49)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Mispricing and alpha coefficients for MOM anomaly in augmented factor models
The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	1.3321*** (16.30)	0.3763*** (5.63)	0.3806*** (8.22)	0.2287*** (6.98)	0.1728*** (6.73)	0.0704*** (3.45)	-0.0016 (-0.07)	-0.1187*** (-5.37)	-0.2483*** (-9.14)	-0.5698*** (-15.72)	-0.9558*** (-17.69)
CAPM+BG α	-0.0089** (-3.09)	0.0075** (3.18)	0.0051** (3.17)	0.0061*** (5.31)	0.0050*** (5.55)	0.0049*** (6.82)	0.0042*** (5.30)	0.0062*** (7.98)	0.0064*** (6.69)	0.0085*** (6.67)	0.0163*** (8.62)
FF3+BG	1.0088*** (9.09)	0.4031*** (4.91)	0.3728*** (6.35)	0.2018*** (4.63)	0.1731*** (4.99)	0.0438 (1.55)	-0.0117 (-0.37)	-0.1119*** (-3.59)	-0.1502*** (-4.62)	-0.3615*** (-7.49)	-0.6057*** (-8.66)
FF3+BG α	-0.0146*** (-4.99)	-0.0017 (-0.78)	-0.0005 (-0.35)	0.0029* (2.55)	0.0029** (3.16)	0.0037*** (4.97)	0.0037*** (4.36)	0.0057*** (6.94)	0.0063*** (6.32)	0.0067*** (5.28)	0.0129*** (7.01)
FF5+BG	1.0711*** (9.46)	0.4981*** (6.54)	0.4246*** (7.35)	0.2218*** (4.94)	0.1856*** (5.16)	0.0304 (1.03)	-0.0463 (-1.42)	-0.1411*** (-4.38)	-0.1818*** (-4.62)	-0.3668*** (-7.26)	-0.5730*** (-7.94)
FF5+BG α	-0.0120*** (-4.15)	0.0022 (1.12)	0.0015 (1.03)	0.0038** (3.28)	0.0034*** (3.73)	0.0037*** (4.87)	0.0030*** (3.58)	0.0052*** (6.30)	0.0058*** (5.80)	0.0069*** (5.32)	0.0142*** (7.69)
CAPM+SY	-1.0553*** (-10.38)	-1.1221*** (-19.71)	-0.6923*** (-15.47)	-0.3882*** (-11.52)	-0.2220*** (-7.95)	-0.0995*** (-4.44)	0.0898*** (3.65)	0.1073*** (4.35)	0.1545*** (4.87)	0.1206* (2.47)	-0.0669 (-0.87)
CAPM+SY α	-0.0034 (-1.04)	0.0135*** (7.37)	0.0088*** (6.13)	0.0082*** (7.53)	0.0062*** (6.86)	0.0054*** (7.50)	0.0037*** (4.67)	0.0056*** (7.09)	0.0056*** (5.47)	0.0079*** (5.05)	0.0169*** (6.87)
FF3+SY	-1.1849*** (-13.24)	-0.9782*** (-16.83)	-0.6158*** (-13.61)	-0.3514*** (-9.96)	-0.1877*** (-6.31)	-0.0775** (-3.17)	0.1341*** (4.96)	0.1645*** (6.22)	0.2277*** (7.14)	0.3086*** (7.34)	0.2067** (3.20)
FF3+SY α	-0.0038 (-1.31)	0.0078*** (4.21)	0.0053*** (3.65)	0.0063*** (5.56)	0.0046*** (4.83)	0.0045*** (5.70)	0.0023*** (2.67)	0.0042*** (4.92)	0.0042*** (4.10)	0.0040** (2.98)	0.0116*** (5.59)
FF5+SY	-1.5370*** (-13.74)	-0.8942*** (-11.97)	-0.6449*** (-11.08)	-0.4343*** (-9.63)	-0.2183*** (-5.70)	-0.1257*** (-4.03)	0.1058** (3.05)	0.1936*** (5.69)	0.3104*** (7.63)	0.5823*** (11.54)	0.6428*** (8.37)
FF5+SY α	-0.0031 (-1.12)	0.0076*** (4.08)	0.0053*** (3.66)	0.0064*** (5.73)	0.0046*** (4.87)	0.0045*** (5.83)	0.0023** (2.70)	0.0041*** (4.82)	0.0040*** (3.93)	0.0034** (2.74)	0.0107*** (5.60)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Mispricing and alpha coefficients for NETSTO anomaly in augmented factor models

The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	0.2016*** (5.19)	-0.0909*** (-3.47)	0.0430* (2.34)	0.0382 (1.63)	-0.0056 (-0.22)	-0.0460* (-2.16)	-0.1454*** (-5.72)	-0.1814*** (-5.75)	-0.2265*** (-6.32)	-0.3778*** (-9.57)	-0.2925*** (-9.07)
CAPM+BG α	0.0033* (2.41)	0.0074*** (8.11)	0.0049*** (7.59)	0.0060*** (7.28)	0.0058*** (6.39)	0.0056*** (7.43)	0.0073*** (8.19)	0.0080*** (7.25)	0.0085*** (6.74)	0.0079*** (5.71)	0.0042*** (3.67)
FF3+BG	0.2245*** (4.13)	-0.0185 (-0.53)	0.0431 (1.66)	0.0017 (0.05)	-0.1076** (-3.01)	0.0090 (0.31)	-0.1037** (-3.04)	0.0279 (0.66)	-0.0725 (-1.51)	-0.2253*** (-4.38)	-0.2430*** (-5.91)
FF3+BG α	0.0049*** (3.45)	0.0054*** (5.83)	0.0047*** (6.91)	0.0058*** (6.55)	0.0048*** (5.02)	0.0044*** (5.67)	0.0052*** (5.79)	0.0070*** (6.32)	0.0062*** (4.93)	0.0044** (3.27)	0.0004 (0.40)
FF5+BG	0.1971*** (3.60)	-0.0170 (-0.46)	0.0175 (0.66)	-0.0165 (-0.50)	-0.1334*** (-3.64)	0.0112 (0.36)	-0.0802* (-2.28)	0.0823* (2.01)	-0.0174 (-0.39)	-0.1655*** (-3.38)	-0.2141*** (-5.30)
FF5+BG α	0.0035* (2.48)	0.0053*** (5.69)	0.0041*** (6.03)	0.0049*** (5.71)	0.0040*** (4.26)	0.0044*** (5.64)	0.0058*** (6.46)	0.0086*** (8.19)	0.0086*** (7.57)	0.0067*** (5.31)	0.0019 (1.80)
CAPM+SY	0.3126*** (7.48)	-0.0640* (-2.20)	0.0777*** (3.86)	0.1148*** (4.54)	0.0576* (2.04)	-0.0407 (-1.72)	-0.1140*** (-3.99)	-0.1685*** (-4.78)	-0.3411*** (-8.92)	-0.4905*** (-11.65)	-0.3766*** (-10.88)
CAPM+SY α	0.0015 (1.14)	0.0078*** (8.33)	0.0045*** (6.88)	0.0055*** (6.60)	0.0055*** (5.98)	0.0058*** (7.62)	0.0080*** (8.65)	0.0090*** (7.92)	0.0104*** (8.44)	0.0107*** (7.88)	0.0063*** (5.64)
FF3+SY	0.2979*** (6.46)	0.0372 (1.22)	0.1001*** (4.50)	0.1458*** (5.20)	0.1045*** (3.39)	0.0185 (0.73)	-0.0248 (-0.83)	-0.1095** (-3.03)	-0.2732*** (-6.83)	-0.3892*** (-9.24)	-0.2608*** (-7.43)
FF3+SY α	0.0016 (1.10)	0.0050*** (5.17)	0.0037*** (5.15)	0.0043*** (4.81)	0.0038*** (3.79)	0.0042*** (5.13)	0.0056*** (5.84)	0.0081*** (6.98)	0.0091*** (7.14)	0.0087*** (6.46)	0.0034** (3.03)
FF5+SY	0.1772** (3.01)	0.0529 (1.35)	0.0402 (1.42)	0.0626 (1.77)	0.0363 (0.92)	0.0405 (1.24)	0.0826* (2.19)	0.1159** (2.66)	0.0126 (0.27)	-0.1947*** (-3.73)	-0.1243** (-2.82)
FF5+SY α	0.0019 (1.27)	0.0050*** (5.13)	0.0038*** (5.36)	0.0045*** (5.07)	0.0040*** (3.98)	0.0041*** (5.06)	0.0054*** (5.74)	0.0076*** (7.01)	0.0085*** (7.23)	0.0083*** (6.41)	0.0031** (2.85)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Mispricing and alpha coefficients for COMPEQ anomaly in augmented factor models

The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	0.0299 (0.60)	-0.3337*** (-8.98)	-0.2011*** (-7.64)	0.0002 (0.01)	-0.0838*** (-3.90)	-0.0023 (-0.10)	-0.0558* (-2.11)	-0.0081 (-0.27)	-0.1812*** (-5.18)	-0.2925*** (-6.68)	-0.3636*** (-9.19)
CAPM+BG α	-0.0007 (-0.38)	0.0079*** (6.10)	0.0072*** (7.85)	0.0054*** (7.18)	0.0064*** (8.48)	0.0059*** (7.36)	0.0069*** (7.46)	0.0069*** (6.46)	0.0080*** (6.51)	0.0097*** (6.33)	0.0086*** (6.20)
FF3+BG	0.1311 (1.89)	-0.1529** (-3.06)	-0.1473*** (-3.97)	-0.0117 (-0.38)	-0.0536 (-1.78)	0.0567 (1.78)	0.0243 (0.69)	0.1003* (2.52)	-0.0561 (-1.24)	-0.1429** (-2.60)	-0.2840*** (-5.62)
FF3+BG α	0.0020 (1.08)	0.0061*** (4.64)	0.0071*** (7.21)	0.0056*** (6.95)	0.0057*** (7.21)	0.0049*** (5.83)	0.0049*** (5.20)	0.0043*** (4.10)	0.0046*** (3.88)	0.0048*** (3.31)	0.0042** (3.12)
FF5+BG	0.1872** (2.59)	-0.0794 (-1.57)	-0.1217*** (-3.17)	-0.0235 (-0.73)	-0.0343 (-1.09)	0.0309 (0.93)	0.0246 (0.67)	0.1062** (2.66)	-0.0387 (-0.87)	-0.0969 (-1.83)	-0.2666*** (-5.11)
FF5+BG α	0.0024 (1.31)	0.0075*** (5.78)	0.0068*** (6.95)	0.0055*** (6.72)	0.0060*** (7.45)	0.0046*** (5.38)	0.0051*** (5.44)	0.0053*** (5.23)	0.0061*** (5.31)	0.0070*** (5.14)	0.0050*** (3.77)
CAPM+SY	0.1824*** (3.34)	-0.1960*** (-4.51)	0.0764* (2.50)	0.0338 (1.42)	-0.0303 (-1.26)	-0.0069 (-0.27)	-0.1507*** (-5.26)	-0.2841*** (-9.20)	-0.3052*** (-8.19)	-0.4737*** (-10.34)	-0.3784*** (-8.57)
CAPM+SY α	-0.0017 (-0.95)	0.0091*** (6.50)	0.0069*** (6.98)	0.0053*** (6.85)	0.0066*** (8.48)	0.0060*** (7.30)	0.0078*** (8.43)	0.0084*** (8.46)	0.0097*** (8.08)	0.0124*** (8.39)	0.0108*** (7.56)
FF3+SY	0.1176 (1.95)	-0.1011* (-2.31)	0.1271*** (3.94)	0.0319 (1.20)	0.0044 (0.17)	0.0513 (1.85)	-0.0699* (-2.29)	-0.2112*** (-6.31)	-0.1845*** (-4.80)	-0.3070*** (-6.66)	-0.2188*** (-4.95)
FF3+SY α	0.0006 (0.31)	0.0074*** (5.26)	0.0059*** (5.75)	0.0053*** (6.23)	0.0058*** (6.84)	0.0043*** (4.86)	0.0055*** (5.66)	0.0063*** (5.92)	0.0066*** (5.35)	0.0081*** (5.51)	0.0068*** (4.77)
FF5+SY	0.2390** (3.10)	0.0758 (1.40)	0.1525*** (3.73)	0.0423 (1.23)	0.0525 (1.56)	0.0294 (0.83)	-0.0559 (-1.42)	-0.1350** (-3.17)	-0.0014 (-0.03)	-0.0638 (-1.12)	-0.1632** (-2.87)
FF5+SY α	0.0004 (0.21)	0.0071*** (5.27)	0.0060*** (5.86)	0.0053*** (6.17)	0.0057*** (6.80)	0.0043*** (4.88)	0.0055*** (5.59)	0.0061*** (5.76)	0.0062*** (5.17)	0.0076*** (5.37)	0.0067*** (4.72)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Mispricing and alpha coefficients for ACCR anomaly in augmented factor models
The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	0.0799 (1.52)	-0.1993*** (-4.92)	-0.1382*** (-4.46)	-0.1735*** (-6.70)	-0.0220 (-1.08)	-0.0737*** (-3.80)	-0.0874*** (-4.63)	-0.1097*** (-4.29)	-0.0937*** (-3.45)	-0.2783*** (-7.90)	-0.2792*** (-6.03)
CAPM+BG α	0.0010 (0.54)	0.0083*** (5.84)	0.0056*** (5.15)	0.0071*** (7.85)	0.0052*** (7.29)	0.0062*** (9.19)	0.0063*** (9.59)	0.0053*** (5.90)	0.0047*** (4.98)	0.0064*** (5.20)	0.0073*** (4.49)
FF3+BG	0.0357 (0.49)	-0.0227 (-2.82)	-0.1223** (-2.82)	-0.1508*** (-4.18)	-0.0185 (-0.65)	-0.0604* (-2.22)	-0.0289 (-1.10)	-0.0344 (-0.98)	0.0293 (0.82)	-0.1386** (-3.15)	-0.0584 (-1.03)
FF3+BG α	0.0045* (2.35)	0.0064*** (4.41)	0.0043*** (3.79)	0.0060*** (6.25)	0.0041*** (5.56)	0.0056*** (7.83)	0.0059*** (8.50)	0.0039*** (4.23)	0.0028** (2.98)	0.0025* (2.18)	0.0019 (1.28)
FF5+BG	0.1321 (1.83)	0.0489 (0.90)	-0.0323 (-0.76)	-0.1129** (-3.03)	0.0071 (0.24)	-0.0514 (-1.80)	-0.0505 (-1.86)	-0.0482 (-1.32)	0.0186 (0.51)	-0.1256** (-2.83)	-0.0832 (-1.68)
FF5+BG α	0.0038* (2.05)	0.0082*** (5.91)	0.0056*** (5.11)	0.0066*** (6.90)	0.0046*** (6.08)	0.0056*** (7.69)	0.0055*** (7.84)	0.0039*** (4.16)	0.0036*** (3.94)	0.0037** (3.27)	0.0044*** (3.49)
CAPM+SY	0.3122*** (5.51)	-0.2215*** (-4.95)	-0.1917*** (-5.67)	-0.0972** (-3.28)	-0.0491* (-2.19)	-0.0350 (-1.61)	0.0354 (1.67)	-0.0602* (-2.10)	-0.1655*** (-5.61)	-0.2380*** (-5.96)	-0.5338*** (-11.28)
CAPM+SY α	-0.0007 (-0.40)	0.0095*** (6.63)	0.0067*** (6.12)	0.0077*** (8.09)	0.0055*** (7.59)	0.0065*** (9.25)	0.0062*** (9.03)	0.0056*** (6.12)	0.0057*** (5.98)	0.0078*** (6.06)	0.0103*** (6.75)
FF3+SY	0.2082*** (3.35)	-0.1394** (-2.94)	-0.1650*** (-4.43)	-0.0481 (-1.51)	-0.0090 (-0.37)	-0.0066 (-0.28)	0.0816*** (3.61)	0.0117 (0.38)	-0.0858** (-2.77)	-0.0663 (-1.72)	-0.3475*** (-7.45)
FF3+SY α	0.0023 (1.16)	0.0079*** (5.18)	0.0062*** (5.18)	0.0066*** (6.50)	0.0043*** (5.41)	0.0058*** (7.58)	0.0051*** (7.05)	0.0038*** (3.93)	0.0033*** (3.69)	0.0034** (2.74)	0.0055*** (3.71)
FF5+SY	0.1149 (1.48)	0.1118 (1.92)	-0.0632 (-1.38)	0.0366 (0.91)	0.0556 (1.78)	-0.0169 (-0.55)	0.0592* (2.04)	0.0307 (0.78)	0.0414 (1.07)	0.1480** (3.12)	-0.0031 (-0.06)
FF5+SY α	0.0028 (1.43)	0.0074*** (5.09)	0.0061*** (5.36)	0.0065*** (6.52)	0.0042*** (5.34)	0.0058*** (7.65)	0.0051*** (7.09)	0.0038*** (3.86)	0.0033*** (3.45)	0.0029* (2.46)	0.0046*** (3.48)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Mispricing and alpha coefficients for NETOPA anomaly in augmented factor models

The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	-0.2913*** (-6.01)	-0.4233*** (-9.93)	-0.3782*** (-11.20)	-0.0972*** (-4.30)	-0.0162 (-0.77)	-0.0193 (-1.01)	0.0089 (0.42)	0.0603** (2.72)	-0.1161*** (-4.90)	-0.1687*** (-6.19)	-0.1319*** (-3.92)
CAPM+BG α	0.0072*** (4.22)	0.0103*** (6.86)	0.0092*** (7.75)	0.0067*** (8.42)	0.0056*** (7.51)	0.0065*** (9.67)	0.0047*** (6.26)	0.0040*** (5.19)	0.0054*** (6.45)	0.0043*** (4.52)	0.0031** (2.62)
FF3+BG	-0.0884 (-1.32)	-0.1209* (-2.17)	-0.2371*** (-5.18)	0.0087 (0.28)	0.0119 (0.40)	-0.0499 (-1.85)	-0.0006 (-0.02)	0.0275 (0.91)	-0.1162*** (-3.64)	-0.1063** (-3.05)	-0.0325 (-0.76)
FF3+BG α	0.0091*** (5.16)	0.0084*** (5.73)	0.0074*** (6.15)	0.0060*** (7.30)	0.0051*** (6.46)	0.0059*** (8.33)	0.0042*** (5.29)	0.0025** (3.10)	0.0033*** (3.97)	0.0013 (1.43)	-0.0007 (-0.62)
FF5+BG	0.0117 (0.17)	-0.0367 (-0.69)	-0.1438** (-3.14)	0.0530 (1.68)	-0.0076 (-0.25)	-0.0651* (-2.31)	-0.0338 (-1.07)	0.0181 (0.58)	-0.0822* (-2.57)	-0.1140** (-3.17)	-0.0484 (-1.27)
FF5+BG α	0.0097*** (5.54)	0.0108*** (7.99)	0.0083*** (7.11)	0.0065*** (8.04)	0.0043*** (5.58)	0.0057*** (7.93)	0.0039*** (4.85)	0.0028*** (3.49)	0.0043*** (5.28)	0.0018 (1.95)	0.0011 (1.16)
CAPM+SY	0.1477** (2.68)	-0.3166*** (-6.37)	-0.1236** (-2.98)	-0.0728** (-2.88)	0.0544* (2.34)	0.0331 (1.56)	0.0408 (1.72)	-0.1199*** (-4.98)	-0.1393*** (-5.34)	-0.1779*** (-5.88)	-0.4643*** (-14.76)
CAPM+SY α	0.0064*** (3.62)	0.0121*** (7.56)	0.0099*** (7.45)	0.0071*** (8.73)	0.0053*** (7.04)	0.0063*** (9.29)	0.0045*** (5.89)	0.0047*** (6.03)	0.0061*** (7.32)	0.0053*** (5.47)	0.0057*** (5.59)
FF3+SY	0.1470* (2.54)	-0.2215*** (-4.65)	-0.0184 (-0.45)	-0.0301 (-1.12)	0.0965*** (3.79)	0.0639** (2.73)	0.0706** (2.69)	-0.0857** (-3.28)	-0.0693* (-2.48)	-0.0556 (-1.83)	-0.3685*** (-11.15)
FF3+SY α	0.0077*** (4.17)	0.0108*** (7.11)	0.0079*** (6.05)	0.0063*** (7.28)	0.0041*** (4.99)	0.0053*** (7.15)	0.0035*** (4.20)	0.0033*** (3.98)	0.0042*** (4.70)	0.0020* (2.07)	0.0031** (2.95)
FF5+SY	0.2972*** (4.13)	0.0991 (1.75)	0.1083* (2.20)	0.0332 (0.98)	0.0087 (0.27)	0.0771* (2.56)	0.0707* (2.11)	-0.0660* (-1.97)	0.0794* (2.32)	0.0276 (0.71)	-0.1981*** (-4.99)
FF5+SY α	0.0076*** (4.23)	0.0102*** (7.25)	0.0078*** (6.38)	0.0062*** (7.32)	0.0043*** (5.30)	0.0053*** (7.07)	0.0035*** (4.16)	0.0032*** (3.88)	0.0039*** (4.59)	0.0018 (1.87)	0.0026** (2.65)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Mispricing and alpha coefficients for INVTOA anomaly in augmented factor models

The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	0.0294 (0.70)	-0.1386*** (-4.57)	0.0817*** (3.39)	-0.0371 (-1.58)	-0.0771*** (-3.59)	-0.1060*** (-5.02)	-0.1412*** (-5.58)	-0.1298*** (-5.13)	-0.2676*** (-8.75)	-0.1856*** (-5.80)	-0.1680*** (-4.40)
CAPM+BG α	0.0030* (2.01)	0.0076*** (7.12)	0.0058*** (6.90)	0.0058*** (7.07)	0.0069*** (9.10)	0.0057*** (7.77)	0.0067*** (7.60)	0.0051*** (5.79)	0.0070*** (6.57)	0.0055*** (4.94)	0.0046*** (3.43)
FF3+BG	-0.0266 (-0.45)	-0.0769* (-2.07)	0.0892** (2.73)	0.0332 (1.02)	-0.0420 (-1.39)	-0.1108*** (-3.79)	-0.1068** (-3.02)	-0.0498 (-1.43)	-0.1415*** (-3.36)	-0.0077 (-0.18)	-0.0503 (-0.98)
FF3+BG α	0.0018 (1.12)	0.0036*** (3.66)	0.0039*** (4.57)	0.0050*** (5.78)	0.0067*** (8.32)	0.0045*** (5.82)	0.0058*** (6.20)	0.0040*** (4.39)	0.0061*** (5.52)	0.0035** (3.13)	0.0018 (1.35)
FF5+BG	0.1198* (2.24)	-0.0054 (-0.15)	0.1193*** (3.74)	0.0825* (2.49)	-0.0419 (-1.34)	-0.0908** (-3.02)	-0.1180** (-3.20)	-0.0103 (-0.31)	-0.1133** (-2.74)	-0.0169 (-0.43)	-0.1252* (-2.53)
FF5+BG α	0.0010 (0.71)	0.0037*** (3.90)	0.0032*** (3.92)	0.0055*** (6.48)	0.0062*** (7.72)	0.0042*** (5.48)	0.0059*** (6.29)	0.0055*** (6.45)	0.0076*** (7.17)	0.0050*** (4.89)	0.0027* (2.16)
CAPM+SY	0.1746*** (3.79)	-0.1275*** (-3.77)	0.0540* (2.01)	-0.0312 (-1.20)	0.0722** (3.03)	0.0095 (0.40)	-0.0713* (-2.49)	-0.2338*** (-8.75)	-0.2039*** (-5.80)	-0.2477*** (-7.12)	-0.3021*** (-7.40)
CAPM+SY α	0.0020 (1.36)	0.0083*** (7.64)	0.0055*** (6.38)	0.0060*** (7.18)	0.0065*** (8.45)	0.0057*** (7.43)	0.0072*** (7.76)	0.0064*** (7.49)	0.0082*** (7.26)	0.0069*** (6.19)	0.0063*** (4.78)
FF3+SY	0.2608*** (5.18)	0.0506 (1.56)	0.1508*** (5.42)	0.0168 (0.59)	0.1103*** (4.25)	0.0778** (3.05)	-0.0271 (-0.87)	-0.2135*** (-7.41)	-0.1675*** (-4.62)	-0.1638*** (-4.59)	-0.2102*** (-5.17)
FF3+SY α	-0.0009 (-0.54)	0.0032** (3.05)	0.0023* (2.58)	0.0047*** (5.25)	0.0056*** (6.73)	0.0038*** (4.69)	0.0062*** (6.24)	0.0063*** (6.81)	0.0080*** (6.92)	0.0052*** (4.51)	0.0040** (2.90)
FF5+SY	0.1423* (2.49)	0.0564 (1.42)	0.0560 (1.62)	0.1025** (2.90)	0.0828* (2.48)	0.0631 (1.95)	0.0083 (0.21)	-0.0636 (-1.79)	0.0276 (0.62)	0.0651 (1.54)	-0.0859 (-1.62)
FF5+SY α	-0.0002 (-0.18)	0.0033*** (3.36)	0.0026** (3.01)	0.0046*** (5.25)	0.0057*** (6.84)	0.0039*** (4.89)	0.0061*** (6.14)	0.0060*** (6.75)	0.0076*** (6.85)	0.0045*** (4.31)	0.0036** (2.70)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: Mispricing and alpha coefficients for DISTRESS anomaly in augmented factor models

The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	0.1328 (1.70)	-0.2160*** (-6.86)	-0.1306*** (-5.66)	-0.0336 (-1.68)	-0.1582*** (-6.98)	-0.0264 (-1.06)	-0.0526 (-1.80)	-0.0844** (-2.73)	-0.2534*** (-6.35)	-0.2777*** (-5.01)	-0.3488*** (-5.17)
CAPM+BG α	-0.0034 (-1.20)	0.0076*** (6.71)	0.0053*** (6.39)	0.0051*** (7.09)	0.0055*** (6.80)	0.0073*** (8.11)	0.0079*** (7.49)	0.0063*** (5.66)	0.0075*** (5.20)	0.0079*** (3.98)	0.0110*** (4.53)
FF3+BG	0.0206 (0.19)	-0.1238** (-2.84)	-0.1099*** (-3.41)	-0.0278 (-0.99)	-0.1724*** (-5.56)	-0.0284 (-0.86)	0.0599 (1.56)	0.0168 (0.41)	-0.0931 (-1.86)	-0.1118 (-1.59)	-0.1443 (-1.67)
FF3+BG α	0.0020 (0.71)	0.0065*** (5.53)	0.0045*** (5.20)	0.0048*** (6.29)	0.0041*** (4.88)	0.0052*** (5.77)	0.0057*** (5.49)	0.0038*** (3.44)	0.0035* (2.56)	0.0023 (1.23)	0.0045 (1.92)
FF5+BG	-0.1232 (-1.16)	-0.1317** (-2.88)	-0.1489*** (-4.49)	-0.0657* (-2.27)	-0.1566*** (-4.83)	0.0026 (0.07)	0.1202** (3.21)	0.0828* (2.04)	-0.0096 (-0.20)	0.0007 (0.01)	-0.0085 (-0.10)
FF5+BG α	-0.0008 (-0.30)	0.0063*** (5.28)	0.0039*** (4.54)	0.0044*** (5.81)	0.0041*** (4.81)	0.0057*** (6.30)	0.0070*** (7.20)	0.0049*** (4.59)	0.0053*** (4.22)	0.0050** (2.83)	0.0071** (3.20)
CAPM+SY	0.9515*** (12.78)	0.1002** (2.75)	0.0658* (2.50)	0.0602** (2.73)	-0.0038 (-0.14)	-0.1351*** (-5.03)	-0.2544*** (-8.40)	-0.3348*** (-10.89)	-0.4991*** (-12.58)	-0.7232*** (-13.66)	-0.8512*** (-13.00)
CAPM+SY α	-0.0081*** (-3.32)	0.0073*** (6.06)	0.0051*** (5.87)	0.0048*** (6.68)	0.0057*** (6.51)	0.0079*** (9.01)	0.0092*** (9.23)	0.0080*** (7.92)	0.0101*** (7.73)	0.0116*** (6.70)	0.0154*** (7.14)
FF3+SY	0.8911*** (10.68)	0.2231*** (5.98)	0.1399*** (4.98)	0.0963*** (3.93)	0.0819** (2.91)	-0.0631* (-2.16)	-0.1819*** (-5.52)	-0.2648*** (-7.91)	-0.3691*** (-9.07)	-0.5677*** (-10.12)	-0.6681*** (-9.61)
FF3+SY α	-0.0066* (-2.49)	0.0045*** (3.76)	0.0033*** (3.68)	0.0039*** (4.96)	0.0035*** (3.91)	0.0058*** (6.22)	0.0074*** (7.00)	0.0063*** (5.88)	0.0072*** (5.49)	0.0080*** (4.44)	0.0112*** (5.00)
FF5+SY	0.9455*** (8.88)	0.3413*** (7.23)	0.1422*** (3.94)	0.1119*** (3.60)	0.1281*** (3.60)	-0.0211 (-0.57)	-0.0499 (-1.22)	-0.2504*** (-5.89)	-0.2490*** (-4.89)	-0.4130*** (-5.86)	-0.6043*** (-6.87)
FF5+SY α	-0.0070** (-2.65)	0.0042*** (3.59)	0.0033*** (3.61)	0.0038*** (4.84)	0.0035*** (3.95)	0.0058*** (6.23)	0.0072*** (6.98)	0.0064*** (6.04)	0.0070*** (5.53)	0.0078*** (4.43)	0.0113*** (5.13)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Mispricing and alpha coefficients for OSCORE anomaly in augmented factor models

The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	1.2291*** (15.99)	-0.1251*** (-5.89)	-0.0886*** (-5.61)	-0.0982*** (-4.77)	-0.0178 (-0.78)	-0.0592* (-2.47)	-0.0577* (-2.00)	-0.2261*** (-6.29)	-0.4216*** (-10.61)	-0.8165*** (-13.42)	-1.3542*** (-17.03)
CAPM+BG α	-0.0125*** (-4.62)	0.0056*** (7.54)	0.0047*** (8.49)	0.0061*** (8.47)	0.0062*** (7.68)	0.0068*** (8.07)	0.0077*** (7.58)	0.0089*** (7.03)	0.0110*** (7.89)	0.0117*** (5.47)	0.0181*** (6.48)
FF3+BG	0.7764*** (9.54)	-0.0122 (-0.42)	-0.0575* (-2.58)	-0.0793** (-2.81)	-0.0233 (-0.76)	-0.0467 (-1.47)	0.0260 (0.76)	-0.0898* (-2.11)	-0.2592*** (-5.89)	-0.3946*** (-5.89)	-0.7887*** (-9.25)
FF3+BG α	-0.0006 (-0.26)	0.0063*** (8.19)	0.0046*** (7.86)	0.0047*** (6.36)	0.0040*** (5.01)	0.0045*** (5.39)	0.0037*** (4.06)	0.0040*** (3.55)	0.0048*** (4.16)	0.0035 (1.96)	0.0069** (3.05)
FF5+BG	0.5056*** (6.83)	-0.0142 (-0.51)	-0.0579* (-2.48)	-0.0727* (-2.48)	-0.0272 (-0.85)	-0.0437 (-1.31)	0.0715* (2.02)	-0.0216 (-0.50)	-0.1955*** (-4.33)	-0.1639** (-2.87)	-0.5198*** (-6.81)
FF5+BG α	-0.0034 (-1.81)	0.0073*** (10.24)	0.0047*** (7.81)	0.0051*** (6.76)	0.0041*** (4.97)	0.0045*** (5.25)	0.0041*** (4.50)	0.0047*** (4.20)	0.0055*** (4.74)	0.0070*** (4.77)	0.0107*** (5.50)
CAPM+SY	0.9329*** (9.71)	-0.0798*** (-3.32)	-0.0278 (-1.55)	-0.0637** (-2.75)	-0.0947*** (-3.79)	-0.0738** (-2.79)	-0.1529*** (-4.89)	-0.2004*** (-4.97)	-0.2511*** (-5.30)	-0.7377*** (-10.35)	-1.0127*** (-10.01)
CAPM+SY α	-0.0178*** (-5.77)	0.0061*** (7.86)	0.0049*** (8.43)	0.0065*** (8.72)	0.0067*** (8.32)	0.0072*** (8.45)	0.0085*** (8.46)	0.0100*** (7.71)	0.0125*** (8.17)	0.0159*** (6.92)	0.0239*** (7.35)
FF3+SY	0.4255*** (5.70)	-0.1019*** (-4.09)	-0.0184 (-0.95)	-0.0035 (-0.14)	-0.0163 (-0.61)	0.0209 (0.75)	0.0172 (0.58)	0.0213 (0.57)	0.0378 (0.95)	-0.3929*** (-6.82)	-0.5274*** (-6.87)
FF3+SY α	-0.0059* (-2.46)	0.0074*** (9.23)	0.0049*** (7.83)	0.0049*** (6.15)	0.0042*** (4.98)	0.0044*** (4.93)	0.0035*** (3.63)	0.0039** (3.27)	0.0048*** (3.77)	0.0080*** (4.32)	0.0132*** (5.39)
FF5+SY	0.2388** (2.90)	0.0559 (1.88)	-0.0148 (-0.59)	0.0702* (2.23)	-0.0143 (-0.42)	0.0274 (0.77)	0.0742 (1.96)	0.1332** (2.89)	0.1701*** (3.50)	-0.0412 (-0.67)	-0.1829* (-2.15)
FF5+SY α	-0.0060** (-2.95)	0.0069*** (9.38)	0.0049*** (7.80)	0.0047*** (6.02)	0.0042*** (4.95)	0.0044*** (4.92)	0.0034*** (3.63)	0.0038** (3.28)	0.0046*** (3.82)	0.0076*** (4.94)	0.0130*** (6.12)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: Mispricing and alpha coefficients for RETONA anomaly in augmented factor models

The coefficient estimates for the 10 decile portfolios are presented in columns (2) through (11) as well as for the hedging portfolio in (1), estimated for the entire period of 1980-2020. The model + mispricing factor row contains the factor's coefficients, while the row below is the portfolio alpha estimate.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
CAPM+BG	0.5178*** (7.50)	-0.2673*** (-9.75)	-0.1894*** (-9.20)	-0.0720** (-3.14)	-0.0329 (-1.59)	0.0297 (1.41)	0.0528* (2.25)	0.0841*** (3.49)	-0.1852*** (-5.16)	-0.4351*** (-8.89)	-0.7851*** (-12.12)
CAPM+BG α	-0.0051* (-2.12)	0.0076*** (7.90)	0.0065*** (8.94)	0.0066*** (8.23)	0.0049*** (6.82)	0.0057*** (7.68)	0.0060*** (7.22)	0.0063*** (7.51)	0.0054*** (4.33)	0.0071*** (4.15)	0.0127*** (5.60)
FF3+BG	0.3487*** (4.08)	-0.0952* (-2.56)	-0.0807** (-2.86)	-0.0083 (-0.26)	-0.0039 (-0.14)	-0.0219 (-0.77)	-0.0235 (-0.73)	0.0629 (1.95)	-0.1686*** (-3.78)	-0.2314*** (-3.91)	-0.4439*** (-5.79)
FF3+BG α	0.0035 (1.55)	0.0081*** (8.28)	0.0062*** (8.39)	0.0060*** (7.13)	0.0035*** (4.75)	0.0041*** (5.38)	0.0042*** (5.02)	0.0042*** (4.90)	0.0007 (0.62)	0.0010 (0.66)	0.0046* (2.29)
FF5+BG	0.0204 (0.28)	-0.1603*** (-4.49)	-0.1110*** (-3.90)	-0.0485 (-1.47)	-0.0134 (-0.45)	-0.0157 (-0.53)	0.0037 (0.11)	0.0920** (2.74)	-0.0355 (-0.85)	-0.0077 (-0.16)	-0.1806** (-2.84)
FF5+BG α	-0.0003 (-0.17)	0.0087*** (9.48)	0.0066*** (9.02)	0.0059*** (7.03)	0.0034*** (4.50)	0.0040*** (5.23)	0.0040*** (4.77)	0.0043*** (5.04)	0.0021 (1.93)	0.0043*** (3.49)	0.0090*** (5.51)
CAPM+SY	1.0580*** (16.31)	0.0251 (0.76)	-0.0049 (-0.20)	0.0210 (0.82)	0.0138 (0.60)	-0.0532* (-2.30)	-0.0939*** (-3.64)	-0.1514*** (-5.81)	-0.4020*** (-11.02)	-0.6643*** (-13.28)	-1.0329*** (-15.42)
CAPM+SY α	-0.0110*** (-5.28)	0.0075*** (7.06)	0.0065*** (8.23)	0.0065*** (7.92)	0.0049*** (6.62)	0.0059*** (7.97)	0.0065*** (7.78)	0.0072*** (8.52)	0.0077*** (6.55)	0.0108*** (6.74)	0.0185*** (8.60)
FF3+SY	0.8347*** (12.75)	0.0553 (1.70)	0.0366 (1.48)	0.0705* (2.55)	0.0903*** (3.74)	-0.0014 (-0.06)	-0.0522 (-1.88)	-0.0946*** (-3.40)	-0.2585*** (-6.89)	-0.4674*** (-9.77)	-0.7794*** (-13.18)
FF3+SY α	-0.0055** (-2.61)	0.0077*** (7.39)	0.0060*** (7.56)	0.0053*** (6.01)	0.0026*** (3.39)	0.0041*** (5.15)	0.0048*** (5.41)	0.0051*** (5.68)	0.0036** (2.98)	0.0061*** (3.98)	0.0132*** (6.95)
FF5+SY	0.7917*** (11.50)	0.2678*** (7.23)	0.1626*** (5.41)	0.1277*** (3.67)	0.1280*** (4.12)	-0.0155 (-0.48)	-0.1533*** (-4.45)	-0.1517*** (-4.27)	-0.2306*** (-5.29)	-0.2235*** (-4.41)	-0.5239*** (-8.13)
FF5+SY α	-0.0059*** (-3.47)	0.0071*** (7.66)	0.0056*** (7.52)	0.0051*** (5.90)	0.0025** (3.26)	0.0041*** (5.20)	0.0051*** (5.93)	0.0052*** (5.92)	0.0038*** (3.47)	0.0059*** (4.68)	0.0130*** (8.10)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 25: Alpha coefficients for anomalies in the CAPM model 1980-1989

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11)) as well as the hedging portfolio of D1-D10 for the period 1980-1989. The finite-sample GRS-tests yield significant result on *** level for each of the 14 anomalies.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0180*** (4.65)	0.0221*** (5.86)	0.0154*** (4.32)	0.0161*** (4.36)	0.0116*** (3.62)	0.0107*** (3.52)	0.0099*** (3.50)	0.0095*** (3.47)	0.0078*** (3.71)	0.0065*** (4.01)	0.0041*** (8.37)
BM	-0.0039 (-0.95)	0.0090** (3.05)	0.0023 (1.12)	0.0006 (0.34)	0.0012 (0.89)	0.0010 (0.73)	0.0021 (1.64)	0.0037* (2.40)	0.0085*** (5.02)	0.0108*** (5.87)	0.0129*** (5.43)
OP	-0.0013 (-0.35)	0.0030 (0.87)	0.0021 (0.79)	0.0032 (1.35)	0.0025 (1.39)	0.0051** (3.29)	0.0008 (0.53)	0.0017 (1.23)	0.0046*** (3.53)	0.0052** (3.31)	0.0043* (2.31)
INV	0.0074* (2.59)	0.0088*** (3.73)	0.0090*** (4.48)	0.0084*** (6.46)	0.0067*** (5.78)	0.0064*** (5.84)	0.0037** (3.32)	0.0038** (2.90)	0.0016 (0.93)	0.0010 (0.55)	0.0014 (0.52)
DP	0.0001 (0.04)	0.0067** (3.03)	0.0055* (2.06)	0.0050* (2.34)	0.0053* (2.55)	0.0057** (2.78)	0.0031 (1.49)	0.0057* (2.29)	0.0047** (3.18)	0.0036* (1.98)	0.0065** (3.06)
MOM	-0.0063 (-1.18)	0.0014 (0.40)	0.0053 (1.87)	0.0076*** (3.40)	0.0053** (3.21)	0.0034* (2.56)	0.0025 (1.92)	0.0053** (3.05)	0.0056** (2.68)	0.0067** (2.76)	0.0077* (2.18)
NETSTO	0.0051* (2.19)	0.0067*** (4.10)	0.0048*** (3.65)	0.0072*** (3.49)	0.0041* (2.15)	0.0044*** (3.89)	0.0039** (3.00)	0.0037* (2.51)	0.0049** (3.01)	0.0018 (1.25)	0.0016 (0.87)
COMPEQ	0.0040 (1.29)	0.0072** (3.11)	0.0095*** (5.12)	0.0052*** (3.55)	0.0050*** (4.39)	0.0036** (2.73)	0.0040** (2.77)	0.0034* (2.09)	0.0029 (1.37)	0.0030 (1.30)	0.0032 (1.44)
ACCR	0.0044 (1.38)	0.0055** (2.64)	0.0038* (2.58)	0.0067*** (5.39)	0.0042*** (3.89)	0.0044*** (4.00)	0.0044*** (3.73)	0.0018 (1.05)	0.0024 (1.40)	0.0012 (0.66)	0.0011 (0.35)
NETOPA	0.0038 (1.51)	0.0049** (2.72)	0.0054** (3.32)	0.0058*** (4.58)	0.0041** (3.33)	0.0060*** (4.60)	0.0040** (2.80)	0.0041** (2.70)	0.0035* (2.36)	0.0031* (2.11)	0.0011 (0.50)
INVTOA	0.0072** (2.88)	0.0072*** (3.89)	0.0074*** (4.40)	0.0066*** (4.28)	0.0065*** (5.54)	0.0055*** (4.19)	0.0021 (1.87)	0.0027* (2.27)	0.0041** (3.23)	0.0018 (0.97)	0.0001 (0.02)
DISTRESS	-0.0024 (-0.59)	0.0021 (1.01)	0.0032* (2.37)	0.0015 (0.93)	0.0048*** (3.64)	0.0072*** (4.96)	0.0066*** (3.53)	0.0046 (1.93)	0.0068* (2.35)	-0.0009 (-0.26)	0.0045 (1.39)
OSCORE	-0.0044 (-1.15)	0.0027** (2.67)	0.0053*** (5.70)	0.0036** (3.35)	0.0043** (3.21)	0.0047** (2.84)	0.0052** (2.79)	0.0075*** (3.52)	0.0041 (1.84)	0.0058* (2.12)	0.0071 (1.97)
RETONA	0.0017 (0.48)	0.0039* (2.17)	0.0039** (2.84)	0.0055*** (3.38)	0.0031* (2.32)	0.0048*** (3.48)	0.0053*** (3.94)	0.0066*** (4.38)	0.0045* (2.33)	0.0074** (3.28)	0.0021 (0.65)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26: Alpha coefficients for anomalies in the FF3 model 1980-1989

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11)) as well as the hedging portfolio of D1-D10 for the period 1980-1989. The finite-sample GRS-tests yield significant result on *** level for each of the 14 anomalies.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0096*** (4.81)	0.0148*** (7.46)	0.0074*** (6.25)	0.0077*** (6.88)	0.0049*** (5.09)	0.0039*** (3.99)	0.0048*** (3.79)	0.0040** (2.73)	0.0032* (2.40)	0.0035** (2.63)	0.0053*** (12.26)
BM	0.0064** (2.80)	0.0121*** (7.41)	0.0063*** (5.00)	0.0035** (2.66)	0.0014 (1.01)	0.0014 (0.94)	0.0008 (0.57)	0.0025 (1.52)	0.0046** (3.08)	0.0055*** (4.03)	0.0057** (3.14)
OP	-0.0095** (-2.87)	-0.0039 (-1.40)	-0.0028 (-1.15)	-0.0000 (-0.01)	-0.0003 (-0.18)	0.0037* (2.42)	-0.0005 (-0.31)	0.0037** (2.88)	0.0036* (2.56)	0.0077*** (4.92)	0.0056** (3.15)
INV	0.0042 (1.47)	0.0059** (2.82)	0.0051** (2.63)	0.0082*** (5.92)	0.0060*** (4.84)	0.0053*** (4.62)	0.0046*** (3.83)	0.0038** (2.71)	0.0019 (1.08)	0.0014 (0.86)	0.0017 (0.83)
DP	0.0028 (0.87)	0.0071** (3.12)	0.0071** (2.81)	0.0039 (1.74)	0.0023 (1.11)	0.0040* (2.10)	0.0029 (1.29)	0.0056* (2.10)	0.0041* (2.57)	0.0015 (0.82)	0.0043* (2.08)
MOM	-0.0177*** (-3.98)	-0.0067* (-2.01)	-0.0008 (-0.29)	0.0039 (1.79)	0.0028 (1.68)	0.0034* (2.39)	0.0028* (2.07)	0.0076*** (4.76)	0.0092*** (5.05)	0.0091*** (4.69)	0.0110*** (4.11)
NETSTO	0.0036 (1.48)	0.0044** (2.66)	0.0048*** (3.48)	0.0058* (2.53)	0.0043* (2.08)	0.0046*** (3.85)	0.0032* (2.47)	0.0022 (1.57)	0.0071*** (4.54)	0.0000 (0.03)	0.0008 (0.46)
COMPEQ	0.0075* (2.39)	0.0090*** (3.85)	0.0110*** (5.58)	0.0072*** (4.73)	0.0046*** (3.81)	0.0038** (2.74)	0.0016 (1.15)	0.0009 (0.57)	0.0004 (0.19)	0.0008 (0.37)	0.0015 (0.75)
ACCR	0.0079* (2.58)	0.0073*** (3.74)	0.0032* (2.00)	0.0079*** (6.14)	0.0033** (2.94)	0.0039** (3.32)	0.0047*** (3.70)	-0.0011 (-0.65)	0.0023 (1.35)	-0.0009 (-0.54)	-0.0007 (-0.29)
NETOPA	0.0049 (1.88)	0.0045* (2.54)	0.0059** (3.35)	0.0070*** (5.21)	0.0044** (3.34)	0.0064*** (4.77)	0.0037** (2.73)	0.0016 (1.05)	0.0012 (0.83)	0.0035* (2.20)	-0.0004 (-0.21)
INVTOA	0.0039 (1.55)	0.0050** (3.15)	0.0043** (2.72)	0.0072*** (4.43)	0.0071*** (6.06)	0.0041** (3.00)	0.0020 (1.63)	0.0020 (1.58)	0.0041** (3.03)	0.0023 (1.40)	0.0011 (0.57)
DISTRESS	0.0039 (1.55)	0.0050** (3.15)	0.0043** (2.72)	0.0072*** (4.43)	0.0071*** (6.06)	0.0041** (3.00)	0.0020 (1.63)	0.0020 (1.58)	0.0041** (3.03)	0.0023 (1.40)	0.0011 (0.57)
OSCORE	0.0025 (1.10)	0.0037*** (3.50)	0.0058*** (5.86)	0.0027* (2.54)	0.0040** (3.37)	0.0031* (2.19)	0.0022 (1.41)	0.0041* (2.28)	0.0017 (1.06)	0.0018 (0.98)	0.0012 (0.60)
RETONA	0.0115*** (3.73)	0.0051** (3.21)	0.0058*** (4.54)	0.0078*** (5.18)	0.0036* (2.59)	0.0047** (3.12)	0.0030* (2.24)	0.0037* (2.55)	-0.0008 (-0.49)	0.0028 (1.36)	-0.0063* (-2.32)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 27: Alpha coefficients for anomalies in the FF5 model 1980-1989

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1980-1989. The finite-sample GRS-tests yield significant result on *** level for 13 anomalies and ** level for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0100*** (4.49)	0.0147*** (6.54)	0.0074*** (5.36)	0.0082*** (6.35)	0.0074*** (7.00)	0.0067*** (6.50)	0.0078*** (5.73)	0.0078*** (4.98)	0.0067*** (4.81)	0.0073*** (5.14)	0.0047*** (9.52)
BM	0.0060* (2.27)	0.0143*** (7.61)	0.0066*** (4.41)	0.0036* (2.34)	0.0034* (2.22)	0.0029 (1.70)	0.0015 (0.96)	0.0027 (1.45)	0.0040* (2.35)	0.0068*** (4.27)	0.0083*** (3.95)
OP	-0.0009 (-0.34)	0.0037 (1.59)	0.0056** (3.13)	0.0072*** (4.14)	0.0032 (1.70)	0.0060*** (3.38)	0.0038* (2.17)	0.0052*** (3.55)	0.0023 (1.49)	0.0060** (3.32)	0.0047* (2.29)
INV	-0.0018 (-0.68)	0.0056* (2.47)	0.0058** (2.85)	0.0060*** (4.27)	0.0043** (3.17)	0.0046*** (3.47)	0.0049*** (3.76)	0.0047** (3.04)	0.0063*** (3.71)	0.0055*** (3.70)	0.0074*** (8.83)
DP	0.0047 (1.23)	0.0070** (2.62)	0.0077* (2.58)	0.0031 (1.21)	0.0048* (2.01)	0.0048* (2.21)	0.0018 (0.67)	0.0031 (1.02)	0.0039* (2.06)	0.0019 (0.85)	0.0024 (0.99)
MOM	-0.0105* (-2.14)	0.0021 (0.59)	0.0060* (2.11)	0.0084*** (3.51)	0.0047* (2.46)	0.0060*** (3.71)	0.0023 (1.42)	0.0069*** (3.76)	0.0072*** (3.46)	0.0070** (3.24)	0.0126*** (4.09)
NETSTO	-0.0028 (-1.08)	0.0032 (1.69)	0.0025 (1.57)	0.0040 (1.49)	0.0041 (1.71)	0.0056*** (4.07)	0.0057*** (3.92)	0.0052** (3.33)	0.0086*** (4.91)	0.0015 (0.86)	0.0060*** (3.45)
COMPEQ	-0.0002 (-0.06)	0.0068* (2.51)	0.0085*** (3.75)	0.0079*** (4.44)	0.0052*** (3.71)	0.0032 (1.95)	0.0022 (1.38)	0.0032 (1.84)	0.0047* (2.05)	0.0048* (1.99)	0.0070** (3.32)
ACCR	0.0056 (1.64)	0.0099*** (4.52)	0.0032 (1.68)	0.0067*** (4.54)	0.0037** (2.78)	0.0034* (2.54)	0.0042** (2.88)	0.0014 (0.79)	0.0048* (2.52)	0.0038* (2.21)	0.0043 (1.78)
NETOPA	0.0046 (1.53)	0.0086*** (4.42)	0.0043* (2.17)	0.0051** (3.30)	0.0060*** (3.96)	0.0062*** (3.93)	0.0053*** (3.39)	0.0016 (0.88)	0.0026 (1.48)	0.0052** (3.08)	0.0040* (2.19)
INVTOA	0.0015 (0.60)	0.0068*** (3.89)	0.0051** (2.97)	0.0069*** (3.68)	0.0071*** (5.29)	0.0033* (2.02)	0.0015 (1.02)	0.0017 (1.15)	0.0057*** (3.75)	0.0064*** (4.13)	0.0053** (2.69)
DISTRESS	0.0003 (0.07)	0.0047 (1.85)	0.0040* (2.35)	0.0014 (0.75)	0.0046** (2.76)	0.0073*** (3.99)	0.0093*** (4.38)	0.0045 (1.61)	0.0101** (3.06)	0.0015 (0.36)	0.0044 (1.25)
OSCORE	-0.0019 (-0.86)	0.0026* (2.22)	0.0052*** (4.54)	0.0048*** (4.02)	0.0058*** (4.28)	0.0055*** (3.39)	0.0056** (3.19)	0.0084*** (4.51)	0.0043* (2.29)	0.0054** (2.69)	0.0045* (2.14)
RETONA	0.0071* (2.44)	0.0076*** (4.26)	0.0066*** (4.55)	0.0084*** (4.76)	0.0031 (1.94)	0.0030 (1.70)	0.0032* (2.05)	0.0057*** (3.44)	0.0015 (0.87)	0.0061** (2.83)	0.0005 (0.19)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 28: Alpha coefficients for anomalies in the CAPM model 1990-1999

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1990-1999. The finite-sample GRS-tests yield significant result on *** level for 13 anomalies and * level for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0144*** (3.67)	0.0202*** (5.08)	0.0173*** (4.04)	0.0199*** (4.49)	0.0193*** (4.06)	0.0182*** (4.29)	0.0162*** (4.03)	0.0149*** (3.92)	0.0109*** (3.71)	0.0083*** (3.81)	0.0057*** (6.30)
BM	-0.0002 (-0.05)	0.0130*** (4.81)	0.0052** (3.00)	0.0035* (2.42)	0.0033* (2.05)	0.0044* (2.27)	0.0027 (1.41)	0.0052* (2.53)	0.0080*** (3.82)	0.0098*** (3.63)	0.0132*** (3.97)
OP	0.0089 (1.79)	0.0141** (3.03)	0.0091** (3.04)	0.0069* (2.14)	0.0064** (2.92)	0.0044 (1.47)	0.0044* (2.03)	0.0054** (2.63)	0.0060** (2.62)	0.0073*** (4.48)	0.0052*** (3.73)
INV	-0.0011 (-0.31)	0.0078*** (3.94)	0.0061*** (3.74)	0.0046** (3.22)	0.0043** (3.27)	0.0030* (2.24)	0.0074*** (5.84)	0.0059** (2.93)	0.0066** (2.76)	0.0112*** (3.40)	0.0089* (2.58)
DP	-0.0057 (-1.42)	0.0033 (0.99)	0.0015 (0.58)	0.0077** (2.80)	0.0096* (2.00)	0.0016 (0.57)	0.0009 (0.33)	0.0053* (2.25)	0.0046 (1.78)	0.0024 (1.37)	0.0090*** (4.06)
MOM	-0.0135* (-1.98)	0.0078 (1.58)	0.0033 (0.92)	0.0022 (0.89)	0.0030 (1.38)	0.0028 (1.85)	0.0033* (1.99)	0.0069*** (4.60)	0.0053** (2.93)	0.0113*** (3.62)	0.0213*** (4.23)
NETSTO	0.0011 (0.35)	0.0075*** (4.44)	0.0034** (2.82)	0.0036 (1.98)	0.0040* (2.17)	0.0040** (3.00)	0.0080*** (4.42)	0.0081*** (3.88)	0.0085** (3.14)	0.0065* (2.15)	0.0064* (2.30)
COMPEQ	-0.0004 (-0.13)	0.0110*** (4.85)	0.0058** (2.98)	0.0049** (3.18)	0.0061*** (3.80)	0.0048** (2.85)	0.0069*** (3.66)	0.0073*** (3.53)	0.0095** (3.00)	0.0103** (2.84)	0.0114*** (3.97)
ACCR	0.0079 (1.96)	0.0118*** (3.49)	0.0077** (3.28)	0.0062*** (4.16)	0.0036* (2.44)	0.0048*** (4.00)	0.0055*** (4.08)	0.0080*** (3.78)	0.0041 (1.94)	0.0055 (1.96)	0.0039 (1.02)
NETOPA	0.0082 (1.91)	0.0116** (3.32)	0.0101*** (4.24)	0.0066*** (4.93)	0.0034** (2.82)	0.0055*** (4.22)	0.0054*** (3.44)	0.0021 (1.25)	0.0061** (3.19)	0.0039 (1.74)	0.0034 (1.18)
INVTOA	0.0035 (1.12)	0.0066*** (3.60)	0.0046** (3.19)	0.0061*** (3.99)	0.0049** (2.78)	0.0060*** (4.53)	0.0058** (3.11)	0.0070*** (3.60)	0.0069* (2.57)	0.0074* (2.52)	0.0032 (1.09)
DISTRESS	-0.0061 (-1.82)	0.0074*** (3.68)	0.0045** (2.91)	0.0061*** (4.54)	0.0043* (2.34)	0.0058*** (3.59)	0.0075** (3.37)	0.0044* (2.16)	0.0085** (2.73)	0.0099* (2.13)	0.0135*** (4.41)
OSCORE	-0.0163* (-2.34)	0.0065*** (3.78)	0.0031** (2.92)	0.0069** (3.35)	0.0058*** (3.94)	0.0064*** (4.28)	0.0050** (2.64)	0.0076** (3.06)	0.0104** (3.34)	0.0152*** (3.70)	0.0228** (2.94)
RETONA	-0.0047 (-1.03)	0.0113*** (4.32)	0.0076*** (4.60)	0.0066*** (3.52)	0.0029 (1.95)	0.0022 (1.66)	0.0044** (3.37)	0.0047*** (3.71)	0.0056 (1.89)	0.0080* (2.47)	0.0160** (3.37)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 29: Alpha coefficients for anomalies in the FF3 model 1990-1999

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1990-1999. The finite-sample GRS-tests yield significant result on *** level for 13 anomalies and * level for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0045* (2.13)	0.0104*** (5.14)	0.0059*** (3.58)	0.0082*** (6.00)	0.0068*** (3.86)	0.0072*** (4.92)	0.0066** (3.12)	0.0065** (2.84)	0.0049* (2.45)	0.0040* (2.49)	0.0059*** (8.57)
BM	0.0063* (2.61)	0.0130*** (8.48)	0.0051*** (3.64)	0.0014 (1.09)	0.0013 (0.86)	0.0014 (0.83)	-0.0002 (-0.13)	0.0024 (1.52)	0.0047** (2.88)	0.0052** (2.67)	0.0067** (3.12)
OP	0.0031 (0.71)	0.0080* (2.24)	0.0045 (1.74)	0.0013 (0.47)	0.0036 (1.73)	-0.0009 (-0.38)	0.0010 (0.53)	0.0028 (1.56)	0.0038 (1.81)	0.0085*** (5.39)	0.0050*** (3.53)
INV	0.0002 (0.05)	0.0051** (2.81)	0.0042** (2.77)	0.0037** (2.67)	0.0034* (2.54)	0.0032* (2.36)	0.0070*** (5.70)	0.0046** (2.70)	0.0043 (1.96)	0.0099*** (3.59)	0.0049 (1.74)
DP	-0.0048 (-1.14)	0.0046 (1.32)	0.0004 (0.15)	0.0067* (2.48)	0.0063 (1.41)	0.0010 (0.35)	-0.0004 (-0.13)	0.0052* (2.11)	0.0058* (2.26)	0.0017 (0.95)	0.0094*** (4.07)
MOM	-0.0187*** (-3.86)	-0.0012 (-0.31)	-0.0026 (-0.86)	-0.0020 (-1.03)	0.0008 (0.39)	0.0009 (0.70)	0.0026 (1.68)	0.0066*** (4.23)	0.0048** (2.93)	0.0086*** (3.72)	0.0175*** (4.97)
NETSTO	0.0043 (1.45)	0.0067*** (3.97)	0.0036** (2.87)	0.0027 (1.46)	0.0034 (1.78)	0.0026* (2.01)	0.0066*** (4.00)	0.0065** (3.21)	0.0058* (2.59)	0.0027 (1.19)	0.0024 (1.06)
COMPEQ	0.0031 (1.05)	0.0101*** (4.50)	0.0060** (3.15)	0.0057*** (3.62)	0.0049** (3.35)	0.0040* (2.27)	0.0050** (2.77)	0.0045* (2.35)	0.0045* (2.00)	0.0050 (1.65)	0.0070** (3.35)
ACCR	0.0124** (3.18)	0.0096** (2.86)	0.0077*** (3.42)	0.0060*** (3.93)	0.0020 (1.41)	0.0042*** (3.43)	0.0045*** (3.43)	0.0065** (3.29)	0.0027 (1.33)	0.0020 (0.80)	-0.0028 (-0.92)
NETOPA	0.0132*** (3.44)	0.0109*** (3.48)	0.0088*** (4.57)	0.0055*** (4.12)	0.0026* (2.16)	0.0055*** (4.13)	0.0044** (2.81)	0.0003 (0.21)	0.0040* (2.24)	0.0017 (0.84)	-0.0022 (-0.98)
INVTOA	0.0052 (1.63)	0.0038* (2.31)	0.0031* (2.26)	0.0058*** (3.68)	0.0056*** (3.44)	0.0057*** (4.14)	0.0053** (3.16)	0.0057** (3.14)	0.0055* (2.22)	0.0035 (1.47)	-0.0013 (-0.52)
DISTRESS	-0.0072* (-2.09)	0.0055** (3.06)	0.0032* (2.17)	0.0057*** (4.41)	0.0031 (1.87)	0.0044** (2.73)	0.0053* (2.53)	0.0016 (0.84)	0.0047 (1.71)	0.0050 (1.13)	0.0126*** (4.39)
OSCORE	-0.0057 (-1.29)	0.0069*** (4.57)	0.0029** (2.65)	0.0046* (2.54)	0.0042** (2.97)	0.0056*** (3.67)	0.0024 (1.36)	0.0043 (1.91)	0.0049* (2.20)	0.0085** (3.12)	0.0126* (2.61)
RETONA	0.0010 (0.24)	0.0116*** (5.16)	0.0065*** (4.24)	0.0042* (2.54)	0.0012 (0.83)	0.0014 (1.06)	0.0034** (2.65)	0.0037** (2.91)	0.0024 (0.92)	0.0042 (1.44)	0.0106** (2.88)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 30: Alpha coefficients for anomalies in the FF5 model 1990-1999

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1990-1999. The finite-sample GRS-tests yield significant result on *** level for 13 anomalies and ** level for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0033 (1.55)	0.0097*** (4.90)	0.0060*** (3.55)	0.0091*** (7.09)	0.0084*** (5.31)	0.0086*** (6.73)	0.0082*** (4.37)	0.0088*** (4.52)	0.0069*** (4.13)	0.0053*** (3.72)	0.0064*** (10.25)
BM	0.0066** (2.70)	0.0145*** (10.12)	0.0057*** (4.28)	0.0022 (1.73)	0.0015 (1.01)	0.0023 (1.44)	-0.0001 (-0.05)	0.0025 (1.51)	0.0057*** (3.80)	0.0062** (3.27)	0.0080*** (3.83)
OP	0.0062* (2.11)	0.0113*** (4.40)	0.0059** (3.37)	0.0034 (1.52)	0.0052** (2.71)	0.0003 (0.15)	0.0027 (1.52)	0.0039* (2.32)	0.0048* (2.35)	0.0099*** (6.94)	0.0051*** (4.03)
INV	-0.0056* (-2.22)	0.0037* (2.26)	0.0038* (2.50)	0.0023 (1.79)	0.0030* (2.27)	0.0035* (2.53)	0.0072*** (5.82)	0.0055** (3.27)	0.0071*** (3.90)	0.0142*** (6.64)	0.0092*** (4.24)
DP	-0.0048 (-1.20)	0.0048 (1.34)	-0.0002 (-0.06)	0.0071** (2.74)	0.0074 (1.65)	0.0008 (0.27)	0.0003 (0.09)	0.0058* (2.31)	0.0061* (2.35)	0.0014 (0.79)	0.0096*** (4.63)
MOM	-0.0165** (-3.36)	0.0044 (1.39)	0.0009 (0.33)	-0.0011 (-0.54)	0.0013 (0.67)	0.0011 (0.82)	0.0026 (1.60)	0.0064*** (4.04)	0.0047** (2.84)	0.0093*** (3.92)	0.0208*** (6.38)
NETSTO	0.0042 (1.40)	0.0082*** (5.01)	0.0029* (2.37)	0.0031 (1.58)	0.0033 (1.69)	0.0033* (2.60)	0.0076*** (4.81)	0.0082*** (4.26)	0.0079*** (4.15)	0.0047* (2.34)	0.0040 (1.83)
COMPEQ	0.0031 (1.06)	0.0116*** (5.27)	0.0060** (3.09)	0.0062*** (3.89)	0.0050** (3.32)	0.0046* (2.57)	0.0060** (3.36)	0.0058** (3.05)	0.0064** (3.28)	0.0073** (2.77)	0.0085*** (4.67)
ACCR	0.0099* (2.58)	0.0119*** (3.64)	0.0073** (3.28)	0.0066*** (4.63)	0.0023 (1.56)	0.0042*** (3.43)	0.0050*** (3.72)	0.0073*** (3.68)	0.0046* (2.39)	0.0045 (1.95)	0.0020 (0.89)
NETOPA	0.0139*** (3.53)	0.0142*** (4.90)	0.0098*** (5.50)	0.0054*** (3.92)	0.0024 (1.92)	0.0053*** (4.17)	0.0047** (2.99)	0.0009 (0.52)	0.0054** (3.24)	0.0039* (2.14)	0.0003 (0.14)
INVTOA	0.0015 (0.53)	0.0031 (1.92)	0.0021 (1.57)	0.0058*** (3.62)	0.0059*** (3.61)	0.0058*** (4.06)	0.0063*** (3.82)	0.0073*** (4.26)	0.0077** (3.26)	0.0066** (3.34)	0.0016 (0.71)
DISTRESS	-0.0073* (-2.07)	0.0071*** (4.20)	0.0043** (2.99)	0.0057*** (4.26)	0.0030 (1.83)	0.0047** (2.93)	0.0063** (3.11)	0.0027 (1.52)	0.0071** (2.99)	0.0095* (2.34)	0.0144*** (5.11)
OSCORE	-0.0072 (-1.83)	0.0086*** (6.32)	0.0024* (2.18)	0.0063*** (3.67)	0.0048** (3.36)	0.0059*** (3.80)	0.0026 (1.46)	0.0057* (2.59)	0.0056* (2.45)	0.0111*** (4.93)	0.0158*** (3.75)
RETONA	0.0010 (0.29)	0.0141*** (7.53)	0.0073*** (4.95)	0.0050** (3.04)	0.0014 (0.93)	0.0013 (0.96)	0.0031* (2.51)	0.0036** (2.91)	0.0035 (1.55)	0.0061** (2.67)	0.0131*** (4.09)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 31: Alpha coefficients for anomalies in the CAPM model 2000-2009

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 2000-2009. The finite-sample GRS-tests yield significant result on *** level for each of the 14 anomalies.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0254*** (6.56)	0.0320*** (7.74)	0.0362*** (6.63)	0.0360*** (7.67)	0.0339*** (6.04)	0.0286*** (5.73)	0.0273*** (5.44)	0.0237*** (5.90)	0.0207*** (5.93)	0.0172*** (5.71)	0.0066*** (5.54)
BM	-0.0260*** (-4.16)	0.0050 (1.53)	0.0041 (1.87)	0.0097*** (4.41)	0.0104*** (6.06)	0.0150*** (6.76)	0.0142*** (6.01)	0.0143*** (6.61)	0.0148*** (6.67)	0.0234*** (6.58)	0.0310*** (6.74)
OP	0.0054 (1.04)	0.0140** (2.83)	0.0109* (2.09)	0.0096** (2.65)	0.0142*** (3.91)	0.0094** (3.01)	0.0102** (2.96)	0.0088*** (3.85)	0.0091*** (4.10)	0.0075*** (4.44)	0.0086*** (5.55)
INV	0.0073 (1.65)	0.0149*** (3.86)	0.0129*** (5.34)	0.0115*** (6.15)	0.0086*** (4.78)	0.0095*** (4.65)	0.0088*** (4.91)	0.0094*** (6.13)	0.0126*** (3.47)	0.0103*** (3.42)	0.0076* (2.17)
DP	-0.0058 (-1.27)	0.0051 (1.49)	0.0094* (2.14)	0.0099** (2.72)	0.0097* (2.46)	0.0085* (2.06)	0.0036 (0.84)	0.0095** (3.03)	0.0100** (3.16)	0.0090* (2.58)	0.0108** (2.75)
MOM	0.0010 (0.10)	0.0191*** (3.40)	0.0130** (3.17)	0.0114*** (4.26)	0.0095*** (4.35)	0.0075*** (4.37)	0.0058** (3.11)	0.0079*** (4.46)	0.0067* (2.59)	0.0098* (2.24)	0.0181** (2.71)
NETSTO	0.0039 (1.22)	0.0106*** (4.16)	0.0073*** (4.59)	0.0080*** (4.30)	0.0101*** (4.87)	0.0109*** (6.33)	0.0125*** (5.43)	0.0141*** (4.65)	0.0127*** (3.88)	0.0139*** (3.44)	0.0067* (2.17)
COMPEQ	-0.0024 (-0.57)	0.0097* (2.29)	0.0091*** (3.53)	0.0077*** (4.32)	0.0097*** (4.73)	0.0101*** (4.90)	0.0120*** (4.68)	0.0125*** (4.47)	0.0124*** (4.56)	0.0167*** (4.08)	0.0121** (3.34)
ACCR	-0.0039 (-0.96)	0.0102** (2.93)	0.0103*** (3.48)	0.0099*** (3.78)	0.0097*** (5.14)	0.0098*** (5.22)	0.0093*** (5.70)	0.0075*** (3.55)	0.0093*** (3.88)	0.0139*** (3.78)	0.0141*** (3.47)
NETOPA	0.0066 (1.56)	0.0133** (2.86)	0.0133** (3.20)	0.0090*** (3.73)	0.0101*** (5.68)	0.0100*** (6.80)	0.0073*** (4.42)	0.0075*** (4.22)	0.0072** (3.29)	0.0089*** (3.50)	0.0068* (2.36)
INVTOA	0.0022 (0.66)	0.0125*** (4.11)	0.0079*** (3.54)	0.0087*** (3.95)	0.0092*** (5.08)	0.0075*** (3.57)	0.0105*** (4.78)	0.0078*** (3.41)	0.0110** (3.33)	0.0103*** (3.77)	0.0103** (3.24)
DISTRESS	-0.0042 (-0.61)	0.0121*** (3.69)	0.0062** (3.09)	0.0075*** (4.72)	0.0087*** (4.19)	0.0129*** (5.58)	0.0127*** (4.96)	0.0105*** (3.83)	0.0090** (2.68)	0.0130** (2.75)	0.0163** (2.62)
OSCORE	-0.0172 (-1.84)	0.0071*** (3.53)	0.0083*** (5.78)	0.0091*** (5.83)	0.0095*** (5.41)	0.0107*** (5.25)	0.0154*** (5.96)	0.0131*** (3.70)	0.0179*** (4.31)	0.0173* (2.09)	0.0243* (2.41)
RETONA	-0.0070 (-1.04)	0.0081*** (3.52)	0.0090*** (4.56)	0.0093*** (5.23)	0.0098*** (6.00)	0.0110*** (6.31)	0.0092*** (5.05)	0.0104*** (4.72)	0.0077* (2.38)	0.0102 (1.82)	0.0151* (2.07)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 32: Alpha coefficients for anomalies in the FF3 model 2000-2009

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 2000-2009. The finite-sample GRS-tests yield significant result on *** level for each of the 13 anomalies and * level for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0055 (1.81)	0.0140*** (4.52)	0.0140*** (4.60)	0.0119*** (6.61)	0.0105*** (5.09)	0.0059** (2.79)	0.0067* (2.53)	0.0079** (3.19)	0.0096*** (4.00)	0.0080** (3.11)	0.0085*** (8.35)
BM	0.0001 (0.01)	0.0085*** (3.50)	0.0080*** (4.73)	0.0078*** (3.39)	0.0054** (2.79)	0.0113*** (4.35)	0.0054* (2.15)	0.0067** (2.86)	0.0055** (2.83)	0.0080* (2.38)	0.0084* (2.07)
OP	-0.0027 (-0.65)	0.0055 (1.61)	0.0077 (1.83)	0.0032 (0.85)	0.0081* (2.14)	0.0024 (0.78)	0.0059 (1.51)	0.0061* (2.33)	0.0099*** (4.00)	0.0077*** (3.71)	0.0082*** (4.35)
INV	0.0010 (0.19)	0.0082* (2.14)	0.0089** (3.09)	0.0068** (3.15)	0.0063** (2.98)	0.0072** (2.90)	0.0103*** (4.70)	0.0087*** (4.60)	0.0076* (2.18)	0.0125*** (4.16)	0.0073* (2.07)
DP	-0.0044 (-0.80)	0.0046 (1.10)	0.0092 (1.96)	0.0072 (1.64)	0.0073 (1.54)	0.0110* (2.32)	0.0039 (0.82)	0.0083* (2.16)	0.0078* (2.01)	0.0081 (1.88)	0.0091 (1.88)
MOM	-0.0146 (-1.60)	0.0043 (0.66)	0.0012 (0.27)	0.0080* (2.52)	0.0055* (2.09)	0.0048* (2.34)	0.0053* (2.32)	0.0067** (3.19)	0.0059* (2.02)	0.0088* (2.27)	0.0188*** (3.49)
NETSTO	0.0022 (0.56)	0.0047 (1.83)	0.0060** (3.17)	0.0082*** (3.66)	0.0069** (2.83)	0.0094*** (4.54)	0.0103*** (3.99)	0.0140*** (4.84)	0.0087* (2.51)	0.0127** (3.37)	0.0025 (0.80)
COMPEQ	-0.0010 (-0.20)	0.0077* (2.25)	0.0117*** (4.44)	0.0071** (3.23)	0.0087*** (3.53)	0.0071** (2.89)	0.0069* (2.35)	0.0088* (2.61)	0.0071* (2.29)	0.0100* (2.38)	0.0087* (2.35)
ACCR	-0.0009 (-0.17)	0.0064 (1.72)	0.0107** (3.19)	0.0094*** (3.55)	0.0098*** (4.24)	0.0085*** (3.94)	0.0084*** (4.45)	0.0079** (3.23)	0.0036 (1.38)	0.0089** (2.70)	0.0073 (1.78)
NETOPA	0.0117** (2.73)	0.0144*** (3.67)	0.0103** (2.81)	0.0077** (2.94)	0.0101*** (4.62)	0.0085*** (4.78)	0.0085*** (4.44)	0.0044* (2.07)	0.0055* (2.21)	0.0024 (1.00)	0.0028 (0.87)
INVTOA	-0.0005 (-0.12)	0.0044 (1.64)	0.0030 (1.15)	0.0065* (2.51)	0.0073** (3.32)	0.0054* (2.40)	0.0096*** (3.80)	0.0066** (2.68)	0.0130*** (4.11)	0.0100** (3.29)	0.0049 (1.33)
DISTRESS	0.0028 (0.35)	0.0101** (2.78)	0.0058* (2.44)	0.0060** (3.12)	0.0059* (2.54)	0.0081** (3.08)	0.0092** (3.10)	0.0097** (3.21)	0.0031 (1.04)	0.0061 (1.31)	0.0073 (1.21)
OSCORE	-0.0081 (-1.37)	0.0094*** (4.43)	0.0088*** (5.55)	0.0073*** (3.96)	0.0052* (2.53)	0.0070** (2.94)	0.0080** (3.09)	0.0052 (1.57)	0.0089* (2.54)	0.0121* (2.30)	0.0175*** (3.13)
RETONA	0.0011 (0.18)	0.0103*** (4.45)	0.0098*** (5.01)	0.0084*** (3.86)	0.0069*** (3.58)	0.0078*** (3.73)	0.0059** (2.71)	0.0051* (2.00)	-0.0009 (-0.29)	0.0041 (1.05)	0.0092 (1.80)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 33: Alpha coefficients for anomalies in the FF5 model 2000-2009

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 2000-2009. The finite-sample GRS-tests yield significant result on *** level for each of the 13 anomalies but insignificant result for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0055 (1.81)	0.0139*** (4.48)	0.0140*** (4.67)	0.0119*** (6.97)	0.0104*** (5.90)	0.0058** (3.02)	0.0066* (2.62)	0.0078** (3.27)	0.0096*** (4.12)	0.0080** (3.24)	0.0085*** (8.75)
BM	0.0002 (0.04)	0.0084*** (3.47)	0.0079*** (4.94)	0.0078*** (3.43)	0.0055** (2.85)	0.0114*** (4.40)	0.0054* (2.14)	0.0068** (2.94)	0.0054** (2.85)	0.0078** (2.77)	0.0083* (2.28)
OP	-0.0031 (-1.10)	0.0052* (2.19)	0.0074* (2.36)	0.0032 (1.11)	0.0079* (2.22)	0.0024 (0.77)	0.0056 (1.66)	0.0061* (2.31)	0.0098*** (4.03)	0.0076*** (3.79)	0.0083*** (4.65)
INV	0.0018 (0.58)	0.0086* (2.59)	0.0093*** (4.23)	0.0069** (3.37)	0.0065** (3.34)	0.0073** (3.23)	0.0104*** (4.94)	0.0087*** (4.60)	0.0073* (2.78)	0.0121*** (5.47)	0.0068** (2.98)
DP	-0.0041 (-0.79)	0.0048 (1.17)	0.0093 (1.97)	0.0072 (1.64)	0.0074 (1.55)	0.0111* (2.33)	0.0040 (0.82)	0.0083* (2.14)	0.0079* (2.12)	0.0079 (1.85)	0.0090 (1.90)
MOM	-0.0151 (-1.80)	0.0037 (0.74)	0.0010 (0.23)	0.0079* (2.51)	0.0054* (2.08)	0.0048* (2.34)	0.0054* (2.47)	0.0067** (3.25)	0.0059* (2.06)	0.0088* (2.26)	0.0188*** (3.48)
NETSTO	0.0024 (0.66)	0.0047 (1.84)	0.0061** (3.29)	0.0084*** (4.63)	0.0071** (3.02)	0.0094*** (4.52)	0.0103*** (3.97)	0.0139*** (4.99)	0.0084** (2.84)	0.0123*** (3.96)	0.0023 (0.78)
COMPEQ	-0.0010 (-0.21)	0.0076* (2.46)	0.0118*** (4.61)	0.0071** (3.27)	0.0087*** (3.64)	0.0072** (2.95)	0.0069* (2.32)	0.0085** (2.74)	0.0070* (2.30)	0.0097* (2.54)	0.0086* (2.33)
ACCR	-0.0005 (-0.11)	0.0063 (1.89)	0.0106*** (3.53)	0.0092*** (3.71)	0.0098*** (4.49)	0.0085*** (3.95)	0.0085*** (4.72)	0.0080*** (3.42)	0.0035 (1.37)	0.0088** (2.68)	0.0069* (2.01)
NETOPA	0.0118** (2.82)	0.0142*** (3.96)	0.0105** (2.94)	0.0076** (3.18)	0.0103*** (5.27)	0.0085*** (4.78)	0.0085*** (4.53)	0.0043* (2.12)	0.0054* (2.23)	0.0024 (0.98)	0.0024 (0.95)
INVTOA	-0.0002 (-0.06)	0.0045 (1.75)	0.0033 (1.46)	0.0064* (2.61)	0.0075*** (3.64)	0.0056* (2.56)	0.0095*** (3.78)	0.0063** (3.00)	0.0128*** (4.34)	0.0098*** (3.46)	0.0047 (1.30)
DISTRESS	0.0035 (0.50)	0.0103** (3.00)	0.0059** (2.65)	0.0060** (3.11)	0.0060* (2.56)	0.0080** (3.12)	0.0090*** (3.40)	0.0097** (3.32)	0.0029 (1.06)	0.0059 (1.39)	0.0068 (1.29)
OSCORE	-0.0084 (-1.65)	0.0091*** (5.18)	0.0087*** (5.66)	0.0074*** (3.99)	0.0052** (2.63)	0.0070** (2.97)	0.0081** (3.25)	0.0053 (1.72)	0.0091** (2.82)	0.0119* (2.60)	0.0175*** (3.59)
RETONA	0.0012 (0.25)	0.0101*** (4.70)	0.0097*** (5.08)	0.0085*** (3.84)	0.0069*** (3.59)	0.0077*** (3.71)	0.0060** (2.85)	0.0051* (1.99)	-0.0008 (-0.31)	0.0039 (1.24)	0.0089* (2.21)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 34: Alpha coefficients for anomalies in the CAPM model 2010-2020

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 2010-2020. The finite-sample GRS-tests yield significant result on *** level for each of the 13 anomalies but insignificant result for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0191*** (4.70)	0.0236*** (5.98)	0.0212*** (5.47)	0.0234* (2.04)	0.0127*** (4.13)	0.0137*** (4.74)	0.0104*** (4.23)	0.0072*** (3.65)	0.0053** (3.05)	0.0062*** (4.97)	0.0045*** (7.80)
BM	0.0009 (0.22)	0.0082*** (4.67)	0.0075*** (4.79)	0.0037** (3.01)	0.0038*** (3.72)	0.0033** (2.73)	0.0025* (2.16)	0.0021 (1.49)	0.0013 (0.67)	0.0021 (0.98)	0.0073* (2.36)
OP	0.0033 (1.39)	0.0077*** (4.12)	0.0108** (3.02)	0.0032 (1.58)	0.0035* (2.01)	0.0005 (0.27)	0.0052*** (3.70)	0.0004 (0.39)	0.0034** (3.26)	0.0066*** (4.72)	0.0044*** (3.92)
INV	-0.0003 (-0.10)	0.0058** (2.94)	0.0067*** (4.08)	0.0052*** (4.78)	0.0011 (0.91)	0.0039*** (3.83)	0.0033** (3.08)	0.0043** (3.08)	0.0056** (3.30)	0.0073*** (3.87)	0.0060* (2.56)
DP	0.0174** (2.63)	0.0101* (2.15)	0.0039 (1.06)	0.0045 (1.09)	0.0007 (0.23)	-0.0009 (-0.24)	0.0031 (0.82)	0.0017 (0.49)	-0.0012 (-0.26)	0.0016 (0.52)	-0.0074 (-1.61)
MOM	-0.0099 (-1.73)	0.0040 (0.91)	0.0009 (0.32)	0.0047* (2.29)	0.0018 (1.27)	0.0055*** (4.51)	0.0036** (3.03)	0.0039** (3.19)	0.0065*** (4.11)	0.0049* (2.36)	0.0140*** (4.11)
NETSTO	0.0015 (0.58)	0.0040** (2.82)	0.0028** (3.11)	0.0045*** (4.74)	0.0041** (3.32)	0.0018 (1.10)	0.0046* (2.57)	0.0073** (3.19)	0.0096*** (3.79)	0.0094** (3.35)	0.0025 (1.21)
COMPEQ	-0.0008 (-0.22)	0.0057** (2.88)	0.0043** (3.18)	0.0031* (2.49)	0.0047*** (3.80)	0.0039** (3.20)	0.0042** (3.21)	0.0049** (2.71)	0.0065** (3.28)	0.0082** (3.19)	0.0065* (2.09)
ACCR	-0.0029 (-0.84)	0.0072** (2.74)	0.0029 (1.69)	0.0060** (3.10)	0.0036** (3.11)	0.0052*** (4.41)	0.0049*** (4.23)	0.0019 (1.63)	0.0021 (1.62)	0.0048** (2.75)	0.0100*** (4.31)
NETOPA	0.0090** (3.18)	0.0116*** (4.46)	0.0076*** (4.31)	0.0055*** (4.66)	0.0034* (2.48)	0.0038** (2.99)	0.0015 (1.26)	0.0020 (1.57)	0.0052*** (4.55)	0.0002 (0.16)	0.0026 (1.67)
INVTOA	-0.0009 (-0.31)	0.0038* (2.32)	0.0029* (2.14)	0.0032** (2.69)	0.0049*** (4.10)	0.0030* (2.58)	0.0070*** (3.88)	0.0047** (2.79)	0.0057*** (4.28)	0.0033* (2.15)	0.0047* (2.02)
DISTRESS	-0.0078 (-1.45)	0.0042*** (3.51)	0.0039** (2.96)	0.0026* (2.31)	0.0039** (3.31)	0.0032* (2.50)	0.0056*** (4.14)	0.0061*** (3.76)	0.0067** (2.99)	0.0078** (3.00)	0.0120* (2.45)
OSCORE	-0.0114* (-2.07)	0.0058*** (4.79)	0.0024* (2.56)	0.0043*** (4.07)	0.0040* (2.38)	0.0047** (3.27)	0.0055*** (3.48)	0.0066** (3.03)	0.0113*** (4.45)	0.0110*** (3.69)	0.0172** (3.28)
RETONA	-0.0138** (-2.97)	0.0056*** (3.79)	0.0044*** (4.46)	0.0043*** (4.31)	0.0032* (2.54)	0.0046*** (3.58)	0.0048* (2.50)	0.0033* (2.12)	0.0055** (2.63)	0.0055* (1.99)	0.0194*** (4.41)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 35: Alpha coefficients for anomalies in the FF3 model 2010-2020

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 2010-2020. The finite-sample GRS-tests yield significant result on *** level for each of the 13 anomalies but insignificant result for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0109*** (3.87)	0.0160*** (5.48)	0.0133*** (5.45)	0.0008 (0.15)	0.0055*** (3.91)	0.0068*** (4.97)	0.0051*** (3.53)	0.0029* (2.48)	0.0021 (1.57)	0.0044*** (4.00)	0.0051*** (9.74)
BM	0.0042 (1.37)	0.0077*** (4.84)	0.0073*** (4.55)	0.0041** (3.35)	0.0035** (3.33)	0.0030* (2.39)	0.0015 (1.35)	0.0013 (0.97)	-0.0001 (-0.07)	0.0000 (0.01)	0.0035 (1.43)
OP	0.0008 (0.34)	0.0058** (3.18)	0.0059 (1.81)	0.0010 (0.53)	0.0020 (1.16)	-0.0004 (-0.22)	0.0044** (3.09)	0.0001 (0.08)	0.0034** (3.14)	0.0071*** (5.01)	0.0050*** (4.38)
INV	0.0002 (0.06)	0.0041* (2.27)	0.0065*** (3.81)	0.0054*** (4.88)	0.0008 (0.62)	0.0037*** (3.58)	0.0032** (2.90)	0.0041** (2.84)	0.0050** (2.86)	0.0075*** (4.21)	0.0039 (1.72)
DP	0.0182** (2.65)	0.0075 (1.57)	0.0020 (0.55)	0.0043 (1.01)	0.0003 (0.10)	-0.0013 (-0.32)	0.0044 (1.13)	-0.0005 (-0.13)	-0.0035 (-0.78)	0.0034 (1.08)	-0.0107* (-2.32)
MOM	-0.0127* (-2.26)	-0.0013 (-0.31)	-0.0023 (-0.83)	0.0029 (1.45)	0.0015 (1.03)	0.0055*** (4.41)	0.0038** (3.12)	0.0037** (2.95)	0.0064*** (3.94)	0.0046* (2.21)	0.0114*** (3.39)
NETSTO	0.0032 (1.23)	0.0036* (2.47)	0.0030** (3.26)	0.0049*** (4.99)	0.0040** (3.25)	0.0007 (0.43)	0.0033 (1.85)	0.0076*** (3.47)	0.0080** (3.12)	0.0072* (2.58)	0.0004 (0.19)
COMPEQ	0.0014 (0.39)	0.0054** (2.62)	0.0040** (2.88)	0.0029* (2.22)	0.0050*** (3.94)	0.0034** (2.74)	0.0037** (2.78)	0.0029 (1.70)	0.0052* (2.57)	0.0055* (2.21)	0.0040 (1.31)
ACCR	-0.0013 (-0.38)	0.0063* (2.35)	0.0022 (1.32)	0.0060** (3.02)	0.0031* (2.60)	0.0058*** (4.77)	0.0047*** (4.01)	0.0009 (0.82)	0.0011 (0.85)	0.0033 (1.92)	0.0076*** (3.42)
NETOPA	0.0080** (2.84)	0.0092*** (3.65)	0.0077*** (4.28)	0.0056*** (4.68)	0.0032* (2.26)	0.0038** (2.88)	0.0015 (1.19)	0.0019 (1.45)	0.0047*** (4.17)	-0.0017 (-1.26)	0.0012 (0.78)
INVTOA	-0.0011 (-0.37)	0.0030 (1.87)	0.0030* (2.12)	0.0026* (2.13)	0.0048*** (3.87)	0.0027* (2.25)	0.0070*** (3.74)	0.0043* (2.46)	0.0054*** (3.98)	0.0020 (1.34)	0.0041 (1.73)
DISTRESS	-0.0004 (-0.07)	0.0052*** (4.43)	0.0039** (2.83)	0.0028* (2.34)	0.0035** (2.94)	0.0026* (2.01)	0.0044** (3.28)	0.0043** (2.76)	0.0045* (2.05)	0.0040 (1.76)	0.0055 (1.25)
OSCORE	-0.0016 (-0.35)	0.0068*** (5.82)	0.0026** (2.72)	0.0042*** (3.94)	0.0032 (1.90)	0.0032* (2.30)	0.0035* (2.51)	0.0034 (1.75)	0.0075** (3.33)	0.0058* (2.37)	0.0083 (1.89)
RETONA	-0.0055 (-1.46)	0.0062*** (4.24)	0.0048*** (4.73)	0.0044*** (4.32)	0.0026* (2.02)	0.0037** (2.93)	0.0046* (2.32)	0.0020 (1.27)	0.0028 (1.47)	0.0016 (0.64)	0.0117** (3.25)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 36: Alpha coefficients for anomalies in the FF5 model 2010-2020

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 2010-2020. The finite-sample GRS-tests yield significant result on *** level for each of the 13 anomalies but insignificant result for DP.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0105*** (3.84)	0.0157*** (5.47)	0.0130*** (5.54)	0.0004 (0.07)	0.0055*** (4.08)	0.0067*** (5.29)	0.0051*** (3.74)	0.0030* (2.55)	0.0021 (1.61)	0.0043*** (4.06)	0.0051*** (9.80)
BM	0.0046 (1.49)	0.0079*** (5.01)	0.0074*** (4.66)	0.0043*** (3.84)	0.0035** (3.27)	0.0028* (2.24)	0.0013 (1.17)	0.0010 (0.77)	-0.0005 (-0.34)	-0.0002 (-0.10)	0.0033 (1.38)
OP	0.0001 (0.06)	0.0052** (3.27)	0.0055 (1.97)	0.0005 (0.29)	0.0018 (1.05)	-0.0005 (-0.26)	0.0044** (3.18)	0.0001 (0.05)	0.0035** (3.19)	0.0075*** (5.62)	0.0050*** (4.59)
INV	-0.0012 (-0.47)	0.0035* (2.08)	0.0060*** (3.89)	0.0050*** (5.15)	0.0005 (0.41)	0.0036*** (3.45)	0.0031** (2.90)	0.0041** (2.78)	0.0054*** (3.61)	0.0078*** (4.93)	0.0047* (2.24)
DP	0.0185** (2.69)	0.0071 (1.47)	0.0021 (0.56)	0.0048 (1.11)	-0.0002 (-0.05)	-0.0014 (-0.36)	0.0041 (1.05)	-0.0006 (-0.17)	-0.0043 (-0.98)	0.0029 (0.97)	-0.0115* (-2.56)
MOM	-0.0123* (-2.23)	-0.0010 (-0.26)	-0.0020 (-0.75)	0.0032 (1.63)	0.0017 (1.16)	0.0056*** (4.46)	0.0036** (3.02)	0.0036** (2.88)	0.0062*** (3.84)	0.0045* (2.18)	0.0112*** (3.45)
NETSTO	0.0036 (1.48)	0.0037* (2.60)	0.0030** (3.31)	0.0049*** (5.15)	0.0036** (3.11)	0.0004 (0.23)	0.0031 (1.86)	0.0079*** (3.75)	0.0082*** (3.43)	0.0073** (2.62)	0.0001 (0.05)
COMPEQ	0.0016 (0.46)	0.0056** (2.69)	0.0040** (2.81)	0.0028* (2.18)	0.0052*** (4.01)	0.0035** (2.83)	0.0037** (2.76)	0.0029 (1.66)	0.0052** (2.70)	0.0055* (2.26)	0.0040 (1.28)
ACCR	-0.0013 (-0.38)	0.0064* (2.47)	0.0021 (1.21)	0.0059** (3.00)	0.0028* (2.44)	0.0057*** (4.67)	0.0046*** (3.91)	0.0011 (0.99)	0.0011 (0.88)	0.0035* (2.10)	0.0077*** (3.68)
NETOPA	0.0083** (2.98)	0.0096*** (4.05)	0.0078*** (4.44)	0.0055*** (4.62)	0.0034* (2.40)	0.0037** (2.78)	0.0013 (1.08)	0.0017 (1.33)	0.0046*** (4.04)	-0.0017 (-1.28)	0.0013 (0.91)
INVTOA	-0.0022 (-0.82)	0.0024 (1.64)	0.0029* (2.06)	0.0023 (1.96)	0.0047*** (3.76)	0.0026* (2.20)	0.0072*** (3.87)	0.0043* (2.49)	0.0056*** (4.12)	0.0021 (1.35)	0.0046* (2.01)
DISTRESS	0.0001 (0.02)	0.0053*** (4.68)	0.0039** (2.77)	0.0028* (2.33)	0.0032** (2.78)	0.0026* (2.00)	0.0043** (3.23)	0.0042** (2.71)	0.0044* (1.99)	0.0038 (1.67)	0.0052 (1.18)
OSCORE	-0.0007 (-0.17)	0.0072*** (6.69)	0.0026** (2.76)	0.0039*** (3.85)	0.0030 (1.78)	0.0029* (2.14)	0.0035* (2.49)	0.0034 (1.79)	0.0073*** (3.76)	0.0056** (2.63)	0.0079* (1.99)
RETONA	-0.0049 (-1.41)	0.0066*** (4.85)	0.0050*** (5.12)	0.0044*** (4.22)	0.0024 (1.89)	0.0034** (2.77)	0.0045* (2.29)	0.0019 (1.18)	0.0024 (1.29)	0.0013 (0.57)	0.0115*** (3.52)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 37: Alpha coefficients for anomalies sorted in BG-normal in the CAPM model

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1980-2020. The finite-sample GRS-test significance along with the estimated F-statistics in parentheses are provided in the last column.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0168*** (7.91)	0.0215*** (10.49)	0.0199*** (8.61)	0.0183*** (8.16)	0.0148*** (7.51)	0.0145*** (8.02)	0.0128*** (7.54)	0.0102*** (7.24)	0.0095*** (7.84)	0.0081*** (8.32)	0.0047*** (10.11)
BM	-0.0040 (-1.71)	0.0060*** (5.73)	0.0049*** (5.29)	0.0043*** (4.64)	0.0043*** (4.83)	0.0043*** (4.23)	0.0052*** (5.04)	0.0070*** (6.56)	0.0058*** (4.94)	0.0069*** (5.59)	0.0100*** (5.77)
OP	0.0015 (0.66)	0.0078*** (3.82)	0.0043** (2.75)	0.0050*** (3.72)	0.0035** (2.59)	0.0054*** (3.96)	0.0038** (3.30)	0.0049*** (5.13)	0.0045*** (4.34)	0.0072*** (7.75)	0.0063*** (7.39)
INV	0.0037 (1.94)	0.0079*** (6.08)	0.0075*** (7.47)	0.0054*** (6.17)	0.0047*** (5.69)	0.0052*** (6.20)	0.0059*** (7.00)	0.0061*** (6.15)	0.0060*** (4.22)	0.0064*** (4.56)	0.0042*** (2.83)
DP	0.0058* (2.18)	0.0082*** (3.95)	0.0062** (2.77)	0.0031 (1.31)	0.0056* (2.48)	0.0067** (2.78)	0.0032 (1.59)	0.0030 (1.58)	0.0064*** (3.40)	0.0029 (1.68)	0.0024 (1.48)
MOM	-0.0108** (-3.06)	0.0038 (1.75)	0.0039* (2.50)	0.0044*** (3.66)	0.0052*** (5.29)	0.0048*** (5.44)	0.0038*** (4.45)	0.0058*** (6.42)	0.0061*** (4.82)	0.0093*** (5.59)	0.0146*** (5.86)
NETSTO	0.0036* (2.25)	0.0069*** (6.59)	0.0044*** (6.27)	0.0058*** (5.81)	0.0058*** (5.98)	0.0045*** (5.46)	0.0059*** (5.75)	0.0073*** (5.79)	0.0076*** (5.07)	0.0068*** (4.75)	0.0033* (2.53)
COMPEQ	0.0000 (0.02)	0.0078*** (4.90)	0.0064*** (6.30)	0.0054*** (6.06)	0.0060*** (6.84)	0.0050*** (5.29)	0.0070*** (6.64)	0.0052*** (4.43)	0.0068*** (5.17)	0.0077*** (4.83)	0.0078*** (5.04)
ACCR	0.0015 (0.76)	0.0068*** (4.58)	0.0053*** (4.49)	0.0063*** (6.37)	0.0054*** (5.83)	0.0049*** (5.77)	0.0062*** (7.13)	0.0044*** (4.20)	0.0044*** (4.02)	0.0057*** (4.04)	0.0054*** (3.09)
NETOPA	0.0074*** (3.58)	0.0093*** (5.45)	0.0085*** (6.51)	0.0057*** (6.45)	0.0056*** (6.54)	0.0046*** (5.61)	0.0045*** (4.96)	0.0042*** (3.96)	0.0043*** (4.28)	0.0035** (3.26)	0.0019 (1.44)
INVTOA	0.0039* (2.27)	0.0068*** (5.95)	0.0048*** (5.01)	0.0050*** (5.23)	0.0068*** (7.45)	0.0048*** (6.42)	0.0059*** (5.56)	0.0064*** (5.41)	0.0051*** (4.48)	0.0056*** (4.06)	0.0029* (2.02)
DISTRESS	-0.0010 (-0.39)	0.0073*** (5.58)	0.0048*** (4.66)	0.0056*** (5.87)	0.0047*** (5.20)	0.0055*** (5.41)	0.0060*** (5.72)	0.0068*** (5.76)	0.0053*** (4.16)	0.0064*** (3.80)	0.0081*** (3.96)
OSCORE	-0.0108*** (-3.41)	0.0054*** (5.88)	0.0041*** (5.72)	0.0061*** (7.96)	0.0060*** (6.50)	0.0055*** (5.71)	0.0075*** (7.07)	0.0069*** (5.13)	0.0112*** (7.85)	0.0124*** (4.62)	0.0162*** (5.02)
RETONA	-0.0005 (-0.19)	0.0076*** (6.28)	0.0074*** (7.56)	0.0056*** (6.10)	0.0065*** (6.77)	0.0044*** (5.05)	0.0052*** (6.05)	0.0051*** (5.48)	0.0047*** (4.82)	0.0042** (2.72)	0.0081** (3.24)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 38: Alpha coefficients for anomalies sorted in BG-normal in the FF3 model

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1980-2020. The finite-sample GRS-test significance along with the estimated F-statistics in parentheses are provided in the last column.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0035** (2.97)	0.0093*** (7.96)	0.0064*** (5.21)	0.0043*** (3.68)	0.0029** (2.97)	0.0037*** (3.53)	0.0033** (3.02)	0.0026** (2.66)	0.0042*** (4.19)	0.0042*** (4.84)	0.0058*** (12.70)
BM	0.0039* (2.07)	0.0072*** (7.80)	0.0055*** (5.97)	0.0038*** (3.94)	0.0029** (3.10)	0.0022* (2.09)	0.0028** (2.69)	0.0036*** (3.48)	0.0029* (2.51)	0.0031** (2.69)	0.0033* (2.16)
OP	-0.0043* (-2.02)	0.0024 (1.30)	-0.0010 (-0.64)	0.0009 (0.72)	0.0003 (0.25)	0.0016 (1.18)	0.0020 (1.71)	0.0040*** (3.99)	0.0041*** (3.70)	0.0084*** (8.69)	0.0067*** (7.43)
INV	0.0026 (1.31)	0.0048*** (3.72)	0.0064*** (6.06)	0.0045*** (4.88)	0.0038*** (4.38)	0.0052*** (5.81)	0.0060*** (6.65)	0.0055*** (5.34)	0.0041** (2.89)	0.0056*** (4.13)	0.0022 (1.48)
DP	0.0051 (1.82)	0.0073** (3.29)	0.0029 (1.24)	0.0014 (0.57)	0.0037 (1.57)	0.0044 (1.76)	0.0021 (1.01)	0.0032 (1.56)	0.0066** (3.30)	0.0027 (1.49)	0.0021 (1.23)
MOM	-0.0144*** (-4.35)	-0.0034 (-1.58)	0.0002 (0.13)	0.0018 (1.46)	0.0035*** (3.45)	0.0038*** (4.10)	0.0040*** (4.40)	0.0056*** (5.88)	0.0062*** (5.05)	0.0080*** (5.27)	0.0111*** (5.12)
NETSTO	0.0042* (2.52)	0.0049*** (4.52)	0.0045*** (6.01)	0.0057*** (5.41)	0.0059*** (5.74)	0.0040*** (4.53)	0.0040*** (3.89)	0.0055*** (4.43)	0.0057*** (3.85)	0.0043** (3.04)	0.0007 (0.54)
COMPEQ	0.0032 (1.57)	0.0068*** (4.33)	0.0065*** (6.15)	0.0059*** (6.22)	0.0059*** (6.33)	0.0041*** (4.09)	0.0049*** (4.51)	0.0028* (2.38)	0.0038** (2.84)	0.0044** (2.86)	0.0035* (2.38)
ACCR	0.0051* (2.51)	0.0053*** (3.51)	0.0052*** (4.20)	0.0056*** (5.31)	0.0050*** (5.11)	0.0047*** (5.25)	0.0059*** (6.54)	0.0028* (2.57)	0.0025* (2.24)	0.0017 (1.24)	0.0002 (0.09)
NETOPA	0.0102*** (4.87)	0.0086*** (5.29)	0.0066*** (5.19)	0.0056*** (6.26)	0.0053*** (5.80)	0.0049*** (5.63)	0.0039*** (4.03)	0.0028* (2.51)	0.0021* (2.04)	0.0008 (0.75)	-0.0016 (-1.23)
INVTOA	0.0035 (1.91)	0.0040*** (3.62)	0.0033** (3.30)	0.0048*** (4.85)	0.0065*** (6.83)	0.0040*** (5.15)	0.0053*** (4.87)	0.0053*** (4.33)	0.0047*** (3.90)	0.0030* (2.27)	0.0006 (0.37)
DISTRESS	0.0021 (0.80)	0.0062*** (4.63)	0.0045*** (4.16)	0.0050*** (5.04)	0.0036*** (3.82)	0.0041*** (3.84)	0.0051*** (4.57)	0.0046*** (3.82)	0.0033* (2.53)	0.0030 (1.84)	0.0039 (1.92)
OSCORE	0.0009 (0.40)	0.0066*** (7.09)	0.0044*** (6.07)	0.0050*** (6.31)	0.0039*** (4.20)	0.0031** (3.15)	0.0046*** (4.36)	0.0025 (1.95)	0.0058*** (4.56)	0.0041 (1.93)	0.0057* (2.43)
RETONA	0.0065** (2.61)	0.0083*** (6.88)	0.0077*** (7.83)	0.0048*** (4.96)	0.0053*** (5.29)	0.0034*** (3.72)	0.0039*** (4.38)	0.0039*** (3.97)	0.0030** (3.00)	-0.0004 (-0.29)	0.0017 (0.77)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 39: Alpha coefficients for anomalies sorted in BG-normal in the FF5 model

The portfolio alphas are estimated for the 10 deciles for each anomaly (D1 through D10 in columns (2) to (11) as well as the hedging portfolio of D1-D10) for the period 1980-2020. The finite-sample GRS-test significance along with the estimated F-statistics in parentheses are provided in the last column.

	(1) D1-D10	(2) D1	(3) D2	(4) D3	(5) D4	(6) D5	(7) D6	(8) D7	(9) D8	(10) D9	(11) D10
Size	0.0037** (3.10)	0.0097*** (8.21)	0.0069*** (5.79)	0.0059*** (5.34)	0.0041*** (4.39)	0.0048*** (4.70)	0.0045*** (4.25)	0.0040*** (4.20)	0.0052*** (5.35)	0.0052*** (6.33)	0.0060*** (12.99)
BM	0.0022 (1.17)	0.0073*** (7.88)	0.0056*** (6.17)	0.0043*** (4.43)	0.0031*** (3.41)	0.0025* (2.35)	0.0033** (3.12)	0.0040*** (3.82)	0.0028* (2.37)	0.0038*** (3.32)	0.0051*** (3.54)
OP	-0.0002 (-0.15)	0.0057*** (4.02)	0.0014 (1.12)	0.0024 (1.93)	0.0018 (1.43)	0.0030* (2.22)	0.0028* (2.39)	0.0041*** (4.08)	0.0047*** (4.31)	0.0080*** (8.41)	0.0060*** (6.86)
INV	-0.0004 (-0.25)	0.0041*** (3.39)	0.0058*** (5.73)	0.0039*** (4.27)	0.0033*** (3.91)	0.0044*** (4.97)	0.0064*** (7.04)	0.0056*** (5.39)	0.0061*** (4.66)	0.0079*** (6.70)	0.0045*** (3.62)
DP	0.0039 (1.37)	0.0060** (2.70)	0.0021 (0.90)	0.0017 (0.67)	0.0038 (1.57)	0.0047 (1.86)	0.0024 (1.11)	0.0027 (1.30)	0.0068*** (3.36)	0.0024 (1.32)	0.0021 (1.20)
MOM	-0.0124*** (-3.77)	-0.0004 (-0.20)	0.0018 (1.20)	0.0023 (1.87)	0.0038*** (3.76)	0.0039*** (4.22)	0.0034*** (3.80)	0.0052*** (5.46)	0.0057*** (4.64)	0.0083*** (5.39)	0.0121*** (5.55)
NETSTO	0.0026 (1.62)	0.0046*** (4.25)	0.0040*** (5.36)	0.0047*** (4.51)	0.0052*** (5.14)	0.0043*** (4.80)	0.0050*** (4.97)	0.0070*** (5.75)	0.0078*** (5.55)	0.0064*** (4.88)	0.0020 (1.62)
COMPEQ	0.0035 (1.66)	0.0080*** (5.21)	0.0061*** (5.71)	0.0057*** (5.93)	0.0064*** (6.87)	0.0039*** (3.87)	0.0051*** (4.69)	0.0038** (3.31)	0.0047*** (3.62)	0.0062*** (4.16)	0.0046** (3.10)
ACCR	0.0033 (1.67)	0.0063*** (4.23)	0.0060*** (4.97)	0.0061*** (5.78)	0.0054*** (5.47)	0.0044*** (4.89)	0.0056*** (6.13)	0.0029** (2.65)	0.0035** (3.22)	0.0032* (2.45)	0.0031* (2.18)
NETOPA	0.0108*** (5.20)	0.0111*** (7.32)	0.0072*** (5.76)	0.0058*** (6.37)	0.0047*** (5.15)	0.0046*** (5.27)	0.0040*** (4.11)	0.0036** (3.29)	0.0028** (2.71)	0.0010 (0.97)	0.0002 (0.20)
INVTOA	0.0027 (1.63)	0.0042*** (3.90)	0.0025** (2.63)	0.0056*** (5.60)	0.0060*** (6.36)	0.0038*** (4.78)	0.0055*** (4.99)	0.0070*** (6.02)	0.0066*** (5.23)	0.0044*** (3.37)	0.0015 (1.05)
DISTRESS	-0.0000 (-0.01)	0.0061*** (4.51)	0.0041*** (3.75)	0.0045*** (4.53)	0.0038*** (4.01)	0.0043*** (4.08)	0.0057*** (5.16)	0.0057*** (4.93)	0.0044*** (3.46)	0.0049** (3.15)	0.0060** (3.08)
OSCORE	-0.0022 (-1.16)	0.0077*** (8.75)	0.0045*** (6.12)	0.0051*** (6.38)	0.0041*** (4.27)	0.0033*** (3.31)	0.0050*** (4.69)	0.0028* (2.21)	0.0066*** (5.20)	0.0066*** (3.36)	0.0099*** (5.31)
RETONA	0.0039 (1.87)	0.0091*** (8.03)	0.0078*** (7.87)	0.0049*** (5.11)	0.0053*** (5.24)	0.0032*** (3.47)	0.0039*** (4.23)	0.0037*** (3.75)	0.0035*** (3.54)	0.0012 (0.94)	0.0052** (2.76)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 40: Alpha coefficients for anomaly hedge portfolios in TSBG-normal

	1980-1989			1990-1999			2000-2009			2010-2020		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
Size	0.0097* (2.37)	-0.0011 (-0.76)	-0.0001 (-0.05)	0.0124** (2.75)	0.0006 (0.28)	-0.0002 (-0.08)	0.0339*** (3.92)	0.0105 (1.57)	0.0108 (1.62)	0.0127*** (3.86)	0.0057** (2.83)	0.0054** (2.73)
BM	-0.0051 (-1.24)	0.0064* (2.31)	0.0018 (0.56)	-0.0026 (-0.54)	0.0054 (1.82)	0.0042 (1.55)	-0.0186*** (-3.68)	0.0012 (0.29)	0.0013 (0.37)	0.0035 (1.00)	0.0068* (2.19)	0.0074* (2.43)
OP	-0.0020 (-0.48)	-0.0104** (-2.69)	0.0023 (0.74)	0.0052 (1.27)	0.0006 (0.15)	0.0027 (1.15)	0.0022 (0.45)	-0.0021 (-0.42)	-0.0026 (-0.75)	0.0004 (0.17)	-0.0018 (-0.76)	-0.0025 (-1.15)
INV	0.0077* (2.39)	0.0034 (1.05)	-0.0019 (-0.62)	-0.0012 (-0.35)	-0.0013 (-0.37)	-0.0062* (-2.34)	0.0057 (1.21)	-0.0014 (-0.25)	-0.0005 (-0.14)	0.0007 (0.24)	0.0013 (0.46)	0.0002 (0.09)
DP	0.0032 (0.91)	0.0067 (1.91)	0.0038 (0.93)	-0.0101* (-2.06)	-0.0082 (-1.62)	-0.0089 (-1.88)	-0.0053 (-0.80)	-0.0060 (-1.75)	-0.0055 (-0.89)	0.0137* (1.99)	0.0163* (2.31)	0.0168* (2.38)
MOM	-0.0065 (-1.30)	-0.0180*** (-4.31)	-0.0085 (-1.88)	-0.0139* (-2.07)	-0.0192*** (-3.64)	-0.0164** (-3.11)	0.0000 (0.00)	-0.0110 (-1.16)	-0.0115 (-1.28)	-0.0064 (-1.18)	-0.0089 (-1.63)	-0.0084 (-1.57)
NETSTO	0.0072* (2.53)	0.0039 (1.43)	-0.0027 (-0.89)	0.0024 (0.76)	0.0057 (1.84)	0.0058 (1.85)	0.0022 (0.62)	0.0001 (0.02)	0.0004 (0.09)	0.0042 (1.67)	0.0049 (1.89)	0.0053* (2.06)
COMPEQ	0.0045 (1.23)	0.0088* (2.34)	-0.0003 (-0.08)	-0.0011 (-0.33)	0.0024 (0.76)	0.0021 (0.67)	-0.0020 (-0.41)	0.0004 (0.08)	0.0004 (0.08)	0.0022 (0.61)	0.0035 (0.97)	0.0037 (1.01)
ACCR	0.0064 (1.91)	0.0113*** (3.42)	0.0062 (1.67)	0.0072 (1.87)	0.0115** (3.06)	0.0084* (2.35)	-0.0029 (-0.65)	0.0013 (0.25)	0.0017 (0.34)	-0.0018 (-0.41)	0.0002 (0.05)	0.0004 (0.09)
NETOPA	0.0044 (1.60)	0.0054 (1.90)	0.0034 (1.06)	0.0092* (2.06)	0.0135*** (3.53)	0.0138*** (3.52)	0.0060 (1.38)	0.0096* (2.08)	0.0098* (2.16)	0.0094** (2.88)	0.0098** (2.90)	0.0099** (2.98)
INVTOA	0.0076* (2.60)	0.0037 (1.25)	0.0026 (0.89)	0.0041 (1.22)	0.0062 (1.83)	0.0027 (0.90)	0.0010 (0.26)	-0.0024 (-0.55)	-0.0022 (-0.53)	0.0000 (0.01)	0.0000 (0.02)	-0.0009 (-0.33)
DISTRESS	-0.0050 (-1.34)	-0.0025 (-0.65)	-0.0022 (-0.48)	-0.0048 (-1.33)	-0.0065 (-1.77)	-0.0070 (-1.85)	-0.0018 (-0.30)	0.0039 (0.56)	0.0045 (0.76)	-0.0009 (-0.20)	0.0051 (1.25)	0.0054 (1.32)
OSCORE	-0.0027 (-0.79)	0.0048 (1.72)	-0.0004 (-0.14)	-0.0109* (-2.24)	-0.0025 (-0.65)	-0.0028 (-0.82)	-0.0117 (-1.28)	-0.0043 (-0.62)	-0.0047 (-0.80)	-0.0031 (-0.60)	0.0055 (1.37)	0.0063 (1.64)
RETONA	-0.0017 (-0.47)	0.0062 (1.83)	0.0003 (0.10)	0.0002 (0.05)	0.0049 (1.21)	0.0052 (1.55)	0.0001 (0.03)	0.0065 (1.14)	0.0066 (1.32)	-0.0012 (-0.31)	0.0035 (1.03)	0.0043 (1.28)

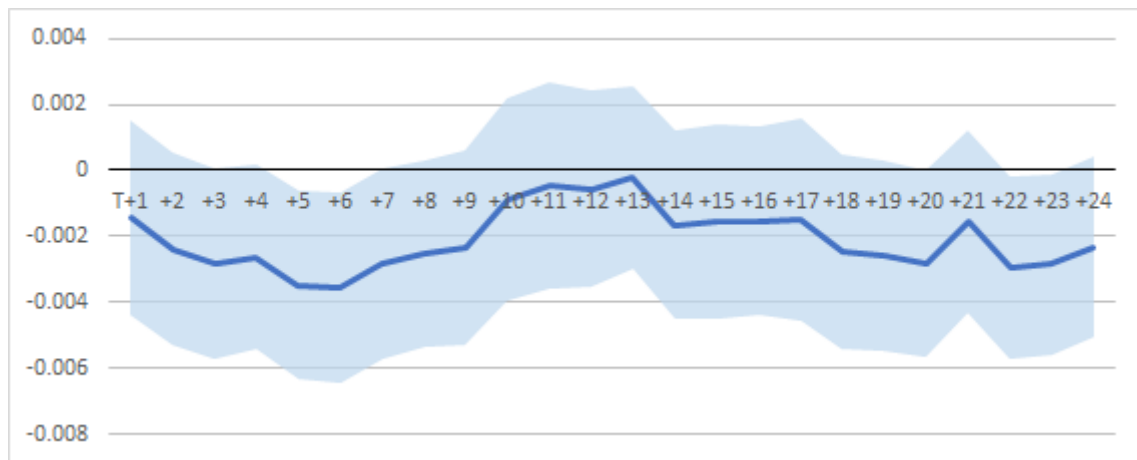
t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 41: Alpha coefficients for anomaly hedge portfolios in augmented TSBG-factor models

	1980-1989			1990-1999			2000-2009			2010-2020		
	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5	CAPM	FF3	FF5
Size	0.0215*** (5.42)	0.0103*** (5.06)	0.0104*** (4.57)	0.0137*** (3.51)	0.0049* (2.26)	0.0039 (1.87)	0.0259*** (6.65)	0.0039 (1.24)	0.0039 (1.22)	0.0176*** (4.14)	0.0091** (3.14)	0.0099*** (3.41)
BM	0.0074* (2.48)	0.0076** (3.33)	0.0070** (2.68)	-0.0038 (-0.98)	0.0060* (2.43)	0.0059* (2.43)	-0.0212*** (-4.97)	-0.0022 (-0.46)	-0.0017 (-0.39)	-0.0060 (-1.67)	-0.0001 (-0.02)	-0.0009 (-0.31)
OP	-0.0006 (-0.16)	-0.0069* (-2.15)	-0.0003 (-0.11)	0.0059 (1.38)	0.0007 (0.18)	0.0053 (1.82)	0.0082 (1.83)	-0.0016 (-0.37)	-0.0035 (-1.20)	0.0019 (0.79)	-0.0006 (-0.27)	0.0012 (0.59)
INV	0.0045 (1.55)	0.0044 (1.46)	-0.0018 (-0.68)	0.0002 (0.05)	-0.0001 (-0.04)	-0.0053* (-2.10)	0.0076 (1.70)	-0.0049 (-0.92)	-0.0005 (-0.15)	0.0038 (1.28)	0.0027 (0.90)	0.0018 (0.73)
DP	0.0025 (0.71)	0.0004 (0.13)	0.0036 (0.99)	-0.0051 (-1.28)	-0.0034 (-0.82)	-0.0043 (-1.05)	-0.0060 (-1.31)	-0.0042 (-0.72)	-0.0025 (-0.45)	0.0115 (1.70)	0.0107 (1.57)	0.0098 (1.42)
MOM	-0.0159** (-3.34)	-0.0183*** (-4.05)	-0.0101* (-2.07)	-0.0085 (-1.61)	-0.0168*** (-3.51)	-0.0148** (-3.05)	-0.0060 (-0.91)	0.0010 (0.12)	-0.0009 (-0.12)	0.0010 (0.19)	-0.0028 (-0.55)	-0.0019 (-0.38)
NETSTO	0.0028 (1.18)	0.0032 (1.31)	-0.0030 (-1.16)	0.0023 (0.77)	0.0055 (1.89)	0.0051 (1.70)	0.0032 (1.02)	0.0048 (1.18)	0.0063 (1.71)	0.0032 (1.20)	0.0052 (1.94)	0.0039 (1.50)
COMPEQ	0.0031 (0.94)	0.0062 (1.92)	-0.0007 (-0.21)	0.0005 (0.16)	0.0032 (1.08)	0.0028 (0.95)	-0.0015 (-0.36)	0.0019 (0.37)	0.0020 (0.40)	0.0006 (0.17)	0.0032 (0.88)	0.0038 (1.01)
ACCR	0.0023 (0.68)	0.0073* (2.39)	0.0044 (1.31)	0.0084* (2.08)	0.0129** (3.26)	0.0107** (2.80)	-0.0043 (-1.04)	-0.0006 (-0.11)	0.0014 (0.29)	-0.0037 (-1.03)	-0.0014 (-0.38)	-0.0015 (-0.40)
NETOPA	0.0020 (0.78)	0.0042 (1.56)	0.0038 (1.27)	0.0069 (1.64)	0.0132*** (3.39)	0.0138*** (3.47)	0.0087* (2.34)	0.0128** (2.84)	0.0138** (3.13)	0.0068* (2.35)	0.0071* (2.39)	0.0084** (2.85)
INVTOA	0.0036 (1.50)	0.0029 (1.14)	0.0003 (0.13)	0.0040 (1.28)	0.0051 (1.59)	0.0020 (0.72)	0.0028 (0.83)	0.0018 (0.45)	0.0035 (0.93)	0.0023 (0.78)	0.0012 (0.38)	-0.0002 (-0.06)
DISTRESS	-0.0014 (-0.32)	-0.0009 (-0.20)	-0.0005 (-0.10)	-0.0056 (-1.67)	-0.0070* (-2.00)	-0.0072* (-2.03)	-0.0052 (-0.75)	-0.0037 (-0.45)	-0.0003 (-0.04)	-0.0095 (-1.70)	-0.0018 (-0.37)	-0.0025 (-0.50)
OSCORE	-0.0083* (-2.24)	0.0016 (0.74)	-0.0015 (-0.68)	-0.0110* (-2.08)	-0.0035 (-0.81)	-0.0061 (-1.55)	-0.0246*** (-4.00)	0.0011 (0.19)	0.0001 (0.01)	-0.0030 (-0.57)	0.0060 (1.48)	0.0042 (1.05)
RETONA	0.0043 (1.14)	0.0095** (3.12)	0.0066* (2.25)	-0.0029 (-0.68)	0.0024 (0.58)	0.0010 (0.28)	-0.0106 (-1.83)	0.0003 (0.06)	0.0012 (0.24)	-0.0074 (-1.65)	-0.0001 (-0.03)	-0.0015 (-0.43)

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 17: The persistence of the BG hedge alpha significance as estimated by FF3



References

- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3-18. doi: [https://doi.org/10.1016/0304-405X\(81\)90018-0](https://doi.org/10.1016/0304-405X(81)90018-0)
- Bartram, S. M., & Grinblatt, M. (2018). Agnostic fundamental analysis works. *Journal of Financial Economics*, 128(1), 125-147.
- Bartram, S. M., & Grinblatt, M. (2021). Global market inefficiencies. *Journal of Financial Economics*, 139(1), 234-259.
- Blitz, D., Huij, J., & Martens, M. (2011). Residual momentum. *Journal of Empirical Finance*, 18(3), 506-521.
- Bondt, W. F. M. D., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40(3), 793-805.
- Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *The Journal of Finance*, 63(6), 2899-2939.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1), 57-82.
- Chen, L., Novy-Marx, R., & Zhang, L. (2011). An alternative three-factor model. *Available at SSRN 1418117*.
- Cooper, M. J., Gulen, H., & Schill, M. J. (2008). Asset growth and the cross-section of stock returns. *the Journal of Finance*, 63(4), 1609-1651.
- Daniel, K., Hirshleifer, D., & Sun, L. (2020). Short-and long-horizon behavioral factors. *The Review of Financial Studies*, 33(4), 1673-1736.
- Daniel, K., & Titman, S. (2006). Market reactions to tangible and intangible information. *The Journal of Finance*, 61(4), 1605-1643.
- Dichev, I. D. (1998). Is the risk of bankruptcy a systematic risk? *the Journal of Finance*, 53(3), 1131-1147.
- Eugene, F., & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2), 427-465.
- Fairfield, P. M., Whisenant, J. S., & Yohn, T. L. (2003). Accrued earnings and growth: Implications for future profitability and market mispricing. *The accounting review*, 78(1), 353-371.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3-56.
- Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. *Journal of Financial Economics*, 82(3), 491-518. doi: <https://doi.org/10.1016/j.jfineco.2005.09.009>

- Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, 63(4), 1653–1678.
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22.
- Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121–1152.
- Hartzmark, S. M., & Solomon, D. H. (2013). The dividend month premium. *Journal of Financial Economics*, 109(3), 640–660.
- Hirshleifer, D., Hou, K., Teoh, S. H., & Zhang, Y. (2004). Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics*, 38, 297–331.
- Hirshleifer, D., & Jiang, D. (2010). A financing-based misvaluation factor and the cross-section of expected returns. *The Review of Financial Studies*, 23(9), 3401–3436.
- Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3), 650–705.
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1), 65–91.
- Jensen, M. C. (1969). Risk, the pricing of capital assets, and the evaluation of investment portfolios. *The Journal of Business*, 42(2), 167–247.
- Loughran, T., & Ritter, J. R. (1995). The new issues puzzle. *The Journal of finance*, 50(1), 23–51.
- McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability? *The Journal of Finance*, 71(1), 5–32.
- Naranjo, A., Nimalendran, M., & Ryngaert, M. (1998). Stock returns, dividend yields, and taxes. *The Journal of Finance*, 53(6), 2029–2057.
- Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, 103(3), 429–453. doi: <https://doi.org/10.1016/j.jfineco.2011.05.003>
- Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1), 1–28.
- Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109–131.
- Pontiff, J., & Woodgate, A. (2008). Share issuance and cross-sectional returns. *The Journal of Finance*, 63(2), 921–945.
- Roll, R. (1977). A critique of the asset pricing theory's tests part i: On past and potential testability of the theory. *Journal of Financial Economics*, 4(2), 129–176.
- Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13, 341–360.

- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3), 425–442.
- Sloan, R. G. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting review*, 289–315.
- Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance*, 70(5), 1903-1948. doi: <https://doi.org/10.1111/jofi.12286>
- Stambaugh, R. F., & Yuan, Y. (2017). Mispricing factors. *The Review of Financial Studies*, 30(4), 1270–1315.
- Theil, H. (1950). A rank-invariant method of linear and polynomial regression analysis. *Indagationes mathematicae*, 12(85), 173.
- Titman, S., Wei, K. J., & Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, 39(4), 677–700.
- Van Binsbergen, J. H., & Opp, C. C. (2019). Real anomalies. *The Journal of Finance*, 74(4), 1659–1706.
- Walkshäusl, C. (2016). Mispricing and the five-factor model. *Economics Letters*, 147, 99-102. doi: <https://doi.org/10.1016/j.econlet.2016.08.025>