

To the memory of Taylan

**BALANCE SHEET CONSERVATIVITY AND CROSS-SECTION OF STOCK
RETURNS**

The Graduate School of Economics and Social Sciences
of
İhsan Doğramacı Bilkent University

by

DÜNDAR ALP ERKENCİ

In Partial Fulfillment of the Requirements for the Degree of
MASTER OF BUSINESS ADMINISTRATION

THE DEPARTMENT OF
MANAGEMENT
İHSAN DOĞRAMACI BİLKENT UNIVERSITY
ANKARA

August 2023

BALANCE SHEET CONSERVATIVITY AND CROSS-SECTION OF STOCK RETURNS

By Dündar Alp Erkenci

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Business Administration.

Ahmet Şensoy
Advisor

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Business Administration.

Fehmi Tanrısever
Examining Committee Member

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Business Administration.

Özge Sezgin Alp
Examining Committee Member

Approval of the Graduate School of Economics and Social Sciences

Refet S. Gürkaynak
Director

ABSTRACT

BALANCE SHEET CONSERVATIVITY AND CROSS-SECTION OF STOCK RETURNS

Erkenci, Dündar Alp

M.S., Department of Management

Advisor: Assoc. Prof. Dr. Ahmet Şensoy

Co-Advisor: Dr. Barış İnce

August 2023

The present study delves into the examination of various balance sheet measures and their significance in the cross-sectional pricing of stocks, to provide unique insights into the understanding of financial risk and its relation to balance sheet metrics. Based on these metrics, our study also sheds light on the importance and stability of a composite factor and its influence on stock prices. The findings of univariate portfolio sorts reveal that BLC (along with its parameters CDA, WCA, and LTDA) is a strong indicator of stock returns, corresponding to statistically significant seven-factor alphas for the high-low portfolios. Consistent results among bivariate portfolio sorts also support the BLC factor strength. The outcomes of Fama-Macbeth regressions for separate BLC parameters indicate positive risk premiums for each parameter when tested against ten different return predictors. Among other balance sheet measures, LTDA is the only BLC parameter associated with the capability to isolate significant risk premiums not proxied by extant anomalies in the literature.

Comprehensive findings that are also supported by the summary statistics collectively indicate mixed effects of risk and underreaction-driven mispricing to explain the abnormal stock returns associated with the high-BLC characteristics of their issuers. The findings reveal high-performing investment strategies based on these metrics, and collectively favor more conservative financial policies for the stock-issuing firms.

Keywords: Balance Sheet Conservativity, Cash-to-Assets Ratio, Financial Risk and Mispricing, Long-Term Debt-to-Assets Ratio, Working Capital-to-Assets Ratio

ÖZET

BİLANÇO İHTİYATLILIĞININ HİSSE FİYATLARINA ETKİSİ

Erkenci, Dündar Alp

Yüksek Lisans, İşletme Fakültesi

Tez Danışmanı: Doç. Dr. Ahmet Şensoy

2. Tez Danışmanı: Dr. Barış İnce

Ağustos 2023

Mevcut çalışma, nakit-varlık oranı, işletme sermayesi-varlık oranı ve uzun vadeli borç-varlık oranı dahil olmak çeşitli bilanço ölçütlerinin hisse fiyatlarına etkisini ölçmekte ve sonuçlar ışığında bilanço ölçütleri ve finansal risk ilişkisine dair özgün bakış açıları sunmayı amaçlamaktadır. Çalışmamız ayrıca, incelenen bilanço ölçütlerinin lineer bir bileşimi olarak oluşturulan bilanço ihtiyatlılığı (BLC) adlı bileşik faktör indeksinin önemini ve hisse senedi fiyatları üzerindeki etkisini vurgulamaktadır. Tek değişkenli portfolyo analizlerinin bulguları, BLC'nin (parametreleri olan nakit-varlık oranı, işletme sermayesi-varlık oranı ve uzun vadeli borç-varlık oranı ile birlikte) hisse getirilerinin güçlü bir göstergesi olduğunu ve ekstrem portfolyolar arasında istatistiksel olarak anlamlı yedi faktörlü alfa farklılıklarına karşılık geldiğini göstermektedir. İki değişkenli portfolyo analizlerindeki tutarlı sonuçlar da BLC faktörünün gösterge gücünü desteklemektedir. BLC parametreleri için Fama-Macbeth regresyonlarının sonuçları, literatürde bilinen on farklı hisse getiri prodüktörüne karşı test edildiğinde de üç

BLC parametresi için de pozitif risk primlerine işaret etmektedir. Bununla birlikte, uzun vadeli borç-varlık oranı, literatürdeki mevcut anomaliler tarafından açıklanamayan, istatistiksel olarak önemli miktarda risk primi izole etme yeteneği ile ilişkilendirilen tek BLC parametresi olarak tespit edilmiştir. Tanımlayıcı istatistik tablolarında özetlenen kapsamlı bulgular, firmaların yüksek-BLC karakteristiği ile korelasyon gösteren anormal hisse senedi getirilerinin oluşmasında hem talep tarafı tepkisizliğiyle tetiklenen yanlış fiyatlandırmaların hem de risk-bazlı etkilerin olası koekzistansına işaret etmektedir. Kolektif bulgular, incelenen bilanço ölçütlere dayalı hisse-yatırım stratejilerinin yüksek performansına vurgu yapmakta ve aynı zamanda hisse senedi ihraç eden firmalar için de daha ihtiyatlı finansal politikaları teşvik etmektedir.

Anahtar Kelimeler: Bilanço İhtiyatlılığı, Nakit-Varlık Oranı, Finansal Risk ve Yanlış Fiyatlama, Uzun Vadeli Borç-Varlık Oranı, İşletme Sermayesi-Varlık Oranı

ACKNOWLEDGMENTS

First of all, I wish to acknowledge my advisor, Assoc. Prof. Dr. Ahmet Şensoy. His guidance through the technical procedures over the past two years has been invaluable. Beyond that, the intellectual contributions and consistent advice he provided, leading up to and throughout this journey, have been a foundation I relied upon greatly.

Also, I would like to explicitly express my deepest gratitude to my co-advisor (and advisor until August 2021), Dr. Barış İnce, for accepting me as his student and guiding me through each and every step of this thesis. I am fully indebted to him, as his patience and endless support made it possible for me to succeed. Honestly, it would be impossible for me to make it through without the master-apprentice relationship we have employed with Dr. İnce since the beginning of this research. I sincerely hope that, in the future as well, I can demonstrate a performance that duly honors his contributions.

Besides, I would like to thank the committee members of my thesis, Assoc. Prof. Dr. Fehmi Tanrısever and Prof. Dr. Özge Sezgin Alp, for reviewing my thesis and providing valuable comments that made it possible to improve my thesis.

I also remain deeply grateful to our faculty's graduate programs coordinator, Ms. Remin Tantoğlu, for her immaculate communication and constant availability for immediate assistance in any time of need.

Moreover, I would like to thank each and every professor whom I have taken courses from, or consulted for advice since I began my higher education at Bilkent University in 2015. For these eight years, each and every one of them has had their unique contributions to the intellectuality of the person who is writing these letters.

Furthermore, I am deeply grateful to my dear friend Anıl for being my closest companion since our high school years. Likewise, I would like to express my profound gratitude to dear Utku, who has been akin to a brother to me, always stepping in with support whenever I was in need.

Last and foremost, I would like to thank my dear mom and dad, for their endless love and unconditional support, which was the main fuel for my motivation to excel in my studies.

TABLE OF CONTENTS

ABSTRACT	iii
ÖZET	v
ACKNOWLEDGMENTS	vii
TABLE OF CONTENTS	ix
LIST OF TABLES	x
 CHAPTER 1: INTRODUCTION	 1
CHAPTER 2: LITERATURE REVIEW	8
CHAPTER 3: RESEARCH QUESTIONS, AIMS AND OBJECTIVES	15
CHAPTER 4: DATA AND METHODOLOGY	19
4.1 Balance Sheet Measures	20
4.2 Balance Sheet Conservativity	24
4.3 Empirical Framework	26
4.3.1 Extension of the Fama-French Five-Factor Model	26
4.3.2 Portfolio Analyses and Fama-MacBeth Regressions	28
CHAPTER 5: EMPIRICAL RESULTS AND DISCUSSION	32
5.1 Univariate Portfolio-Level Analyses	32
5.1.1 Cash-to-Assets (CDA)	33
5.1.2 Working Capital-to-Assets (WCA)	33
5.1.3 Long-Term Debt-to-Assets (LTDA)	34
5.1.4 Balance Sheet Conservativity Factor (BLC)	35
5.2 Bivariate Portfolio-Level Analyses	36
5.2.1 Size	38
5.2.2 Illiquidity	40
5.2.3 Mispricing	41
5.3 Summary Statistics	44
5.4 Fama-Macbeth Regressions	50
5.5 Societal Impact	52
CHAPTER 6: CONCLUSION	53
REFERENCES	57

LIST OF TABLES

1.	Univariate Portfolio Analysis of Stocks Sorted by CDA.....	33
2.	Univariate Portfolio Analysis of Stocks Sorted by WCA.....	34
3.	Univariate Portfolio Analysis of Stocks Sorted by LTDA.....	35
4.	Univariate Portfolio Analysis of Stocks Sorted by BLC	36
5.	Bivariate Portfolio Analysis of Stocks on 5x3 Sorted Portfolios (Size).....	38
6.	Bivariate Portfolio Analysis of Stocks on 5x3 Sorted Portfolios (Illiquidity)	40
7.	Bivariate Portfolio Analysis of Stocks on 5x3 Sorted Portfolios (Mispricing).....	43
8.	Median for Portfolios Sorted by CDA	45
9.	Median for Portfolios Sorted by WCA	46
10.	Median for Portfolios Sorted by LTDA.....	47
11.	Median for Portfolios Sorted by BLC.....	48
12.	Fama-MacBeth (Multivariate) Regression Results.....	51

CHAPTER 1

INTRODUCTION

Balance sheet analyses are frequently used by various parties (including investors and lenders) to evaluate the performance and financial health of a firm as they offer valuable insights into a firm's profitability, liquidity, efficiency, and solvency. Indeed, the analysis of each statement is instrumental in making investment decisions and effectively managing portfolios, as it reveals crucial information about the subject company's characteristics. Some of this information may show characteristics unique to the subject company (i.e., fingerprints), and some may follow a certain pattern that is observable in other subjects of interest (e.g., size). The latter is useful for the scope of this research as such information can be represented by what we call "balance sheet measures." Given that sufficient data are available, these measures can easily be used to group the stocks of an entire market under ranked portfolios. It is not a new practice for finance scholars to employ analyses and estimations based on such measures. Owing to the widely accepted theoretical phenomena of the risk-return tradeoff and the Efficient Market Hypothesis (EMH), many studies have aimed to explain their impact on stock returns by testing the capacity of the respective measures to generate risk-adjusted excess returns. While this research intends to do so, the balance sheet measures in this study were deliberately chosen with the theoretical motivation to deliver a unique prospect to the understanding of financial risk without overlooking behavioralist explanations related to stock mispricing. Deliberation on the choice of measures stems from a seemingly logical attachment of

a supposed level of riskiness to a certain characteristic of stocks (i.e., balance sheet conservativity). This characteristic of holding more cash and working capital and less long-term debt may reasonably be understood as a sign of “low-risk,” and, accordingly, lower expected stock returns. However, inversely, issuers of riskier stocks may also yield more conservative corporate policies to tackle risk, which may be reflected in their announced balance sheets.

Regardless of these tricky causal attachments and theoretical motivations, this study’s empirical framework is directly related to the concept of risk-return tradeoff and risk factors as it follows a mainstream risk factor model based on the Fama-French framework (Fama & French, 2015). Therefore, understanding not only the fundamentals of balance sheet measures and stock markets but also the dynamics and development of risk factor models is vital to introduce our thesis. These developments include extensive research and theories that have been developed since the mid-1900s that allow us, with persistent effort, to comprehend stock behavior. Over the years, numerous efforts have culminated in the development of several widely-recognized asset pricing models. Foremost among these is the Capital Asset Pricing Model (CAPM) introduced by Sharpe (1964) and Lintner (1965). While the model comes with various assumptions and variations, which will be elaborated upon in the literature review, its fundamental tenet posits a positive relationship between an asset's market beta (its sensitivity to market risk) and its expected returns, encapsulating the risk-return tradeoff. On the other hand, although the CAPM was a historical development that literally marked the beginning of the asset pricing theory, its empirical failures that are reported in various research (e.g., Fama & French, 1992) exposed its limitations in explaining the risk-return relationship. Of

those limitations, what primarily concerns the introduction part of this research is its inability to foresee the other sources of risk. However, as financial markets were (as they are now) dynamic and constantly evolving, collaboration among researchers, investors, financial institutions, and analysts was necessary to develop improved models and theories that could explain risk-return relationships with fewer pricing irregularities and greater accuracy. As a result, more complex models have been established by prominent researchers, including the famous early examples of Intertemporal CAPM (I-CAPM) by Merton (1973) and the Arbitrage Pricing Theory (APT) by Ross (1976). Both research paved the theoretical way for the establishment of the multi-factor models we still use today. In fact, the APT was originally developed as a multi-factor model, but it did not (nor intended to) specify the risk factors. Years later, a subject-relevant milestone in this regard was the development of the Fama-French Three-Factor Model (FF3) by Fama and French in 1993, which was a three-factor model based on size (SMB, i.e., Small-Minus-Big) and value (HML, i.e., High-Minus-Low) risk factors, in addition to the market risk.

The parallel developments to these factor models and their successors will be discussed in more detail in the literature review. However, it should also be mentioned that these models have opened up new avenues for researchers to explore various factors that have a strong relationship with average stock returns. One such factor that has gained attention in recent years is profitability. Novy-Marx (2013) identified profitability as a risk factor capable of generating excess returns for investors. The study employed gross profit over total assets as a criterion for profitability and found it to be a significant factor for estimating projected returns. Another factor that has been studied in recent years is the investment factor. Aharoni,

Grundy, and Zeng (2013) demonstrated that there is a strong (negative) relationship between investment and cross-sectional stock returns. This finding has been supported by several studies before, including those conducted by Fama & French (2008), and Watanabe, Xu, Yao & Yu (2013).

Many other well-known anomalies in the finance literature, such as size, value, and momentum, have also been studied extensively. Such anomalies can persist during specific periods, being detectable at certain times and subsequently disappearing, whereas others may occur more frequently. According to Schwert (2003), value and size premiums have vanished as a result of studies exposing them to investors, which suggests that market participants started exploiting risk premiums, leading to the disappearance of the anomalies. This research also indicates that investors acquire knowledge about mispricing. On the other hand, some factors can vanish if some behavioral (or institutional) biases may prevent them from completely eradicating mispricing in the market, resulting in “pricing anomalies”, which correspond to abnormal returns that cannot be explained by the existing risk-factor models (i.e., mispricing). Such explanations for mispricing include investor sentiment (Barberis, Shleifer, & Vishny, 1998), costly arbitrage related to high transaction and holding costs (Pontiff, 2006), investor inattention (Loh, 2010), limits to arbitrage (Gromb & Vayanos, 2010), et cetera. Fama (1991) pointed out his view on the occurrence of such return anomalies by acknowledging the ambiguity between challenging explanations of market imperfections and inaccurate models. Hence, there is always room for a dilemma to address those pricing anomalies: inadequate models and/or behavioralist explanations. Literature evolved on both aspects to dissipate those anomalies that consistently persist, such as the momentum anomaly that was

discovered by Jegadeesh and Titman (1993), which captured the one-year momentum effect of the return differences between outperforming and underperforming stocks of the recent past. As a consequence, based on the Fama-French three-factor model, Carhart (1997) created a four-factor model (FFC) and incorporated the momentum factor into the FF3 model, and showed that this four-factor model significantly reduces the mispricing patterns of the existing models.

In response to the empirical shortcomings of the FF3, Fama and French (2015) introduced the Fama-French five-factor asset pricing model (FF5). According to their research, the three-factor model explaining stock returns was significantly less effective than the new five-factor model. Along with considerations for size and value risk, they added investment (CMA, i.e., Conservative-Minus-Agressive) and profitability (RMW, i.e., Robust-Minus-Weak) measures to their model, in accordance with the previous studies mentioning the need for the integration of investment and profitability factors to FF3. However, their reluctance to include the momentum factor (commonly interpreted as UMD, i.e., Up-Minus-Down) in their model did not prevent prominent researchers from utilizing it as part of an augmented model based on FF5. Hence, in 2018, while admitting their justifiable reluctance to “opening the game of factors”, Fama and French themselves introduced and tested the efficacy of the popular six-factor, momentum-augmented model (FF5+UMD) against various models such as the FF5, FFC, and FF3. The long-awaited endorsement of the momentum factor by these two well-renowned scholars contributed to the popularity of the six-factor model, which has since become the basis for many studies in asset pricing literature. However, it also

catalyzed empirical researchers' tendency to focus efforts on the inclusion of additional factors that could capture the remaining price anomalies, resulting in an "influx" of new factors and return predictors. Our study aims to distinguish itself with a solid theoretical emphasis on developing a unique understanding of financial risk and the risk-associated patterns of conservative balance sheet policies. Hence, a solid theoretical motivation and curiosity underlie our search for empirical robustness for the measures' effectiveness.

Theoretically, a factor based on balance sheet measures could be a new candidate for an additional factor to reduce such anomalies, given that a wealth of information is available in each announced balance sheet of any company. Moreover, in recent years, the significance of balance sheet measurements and cross-sections of stock returns has endured. Studies that have expanded on previous risk factor models seeking to assess the importance of balance sheet measurements in explaining the cross-section of stock returns will be examined in the literature review section. In accordance with the papers studied, we expect that our study will provide key insights and contribute to the existing literature to determine whether the examined balance sheet metrics – cash-to-assets (CDA), working capital-to-assets (WCA), and long-term debt-to-assets (LTDA) ratios – are associated with significant risk-adjusted excess return differences (i.e., factor alphas) among the ranked portfolios and whether they are capable of generating isolated risk premiums among the ranked portfolios and whether they are capable of generating isolated risk premiums (namely λ_{CDA} , λ_{WCA} , λ_{LTDA}) for the individual stocks, when tested against the well-known return predictors. Moreover, as the measures of interest in this study were chosen deliberately to indicate a certain characteristic of a stock (i.e., balance

sheet conservativity), the related to their composite factor (BLC) has its theoretical justification for being included in the portfolio-level analyses.

The remaining sections of the study are structured as follows: Chapter 2 provides a brief review of the existing literature. Chapter 3 presents the objectives, research questions, and aims of our study. Chapter 4 elaborates on the data, methodology, and empirical framework. Chapter 5 presents the empirical results and the ensuing discussion. Finally, Chapter 6 concludes the study.

CHAPTER 2

LITERATURE REVIEW

Various recent studies have approached this topic from diverse angles and have shed light on the connection between balance sheet measures and stock returns. In recent years, scholars have used various theoretical and empirical approaches to the impact of balance sheet measures on stock returns. In order to assess the outcomes, more accurate and complex models have been developed in years as a result of the anomalies in the actual data. Chapter 1 briefly provides essential background for some of these models. Nevertheless, as mentioned in the introduction section, parallel approaches and developments also shed light on modern asset pricing research.

Relevant developments included not only the addition of new factors but also the relaxation of some strict assumptions of the CAPM. For instance, while the traditional CAPM assumed that there are no market imperfections, such as taxes, Brennan (1970) modeled taxes into CAPM. While his model included only proportional taxes, Litzenberger and Ramaswamy (1979) contributed to this extension by incorporating progressive taxes. Nevertheless, decades after those tax-CAPM models, a considerable challenge to such extensions in support of the traditional CAPM came from Kruschwitz and Löffler (2009). They criticized those “Tax-CAPM” models for not accounting for the redistribution effect. The authors claimed that treasures typically redistribute those tax revenues back, and the

combined effect of this distribution is significant enough to completely deduct the conception of taxes from CAPM. And indeed, those tax-CAPM models assume that tax payments of investors simply “disappear” from the universe. Of course, it is not under the scope of this research (and its literature review) to examine whether such “disappearances” occur in the real world or not. However, as Kruschwitz and Löffler themselves admitted, complex (or “richer”) tax systems that include other sources of taxation would challenge their results (2009). Likewise, such a taxation system (like the ones in the real world) may have lower share and cumulative redistributive effects of dividend and Capital Gains Tax (CGT) revenues. It can also be objectively noted that the research did not include any discussion of challenging assumptions, such as neoclassical views that stress the incapability (or even unwillingness) of state-run redistribution mechanisms such as treasuries. On the contrary, Kruschwitz and Löffler assumed a capable treasury that was sufficiently competent to eradicate the tax anomaly (2009). It must also be noted that the discussion related to the effect of capital taxation on stock returns is not constricted to CAPM vs. tax-CAPM in the literature. For instance, a 2008 study on the US case of 1997 Taxpayer Relief examined the relationship between CGT shocks and stock returns (Dai, Maydew, Shackelford, & Zhang). Their empirical analyses showed a significant increase in average stock prices during the week following the announcement of the CGT cut, due to the dominance of the capitalization effect (increase in demand) over the dominance of the lock-in effect (increase in supply). For instance, a 2008 study on the US case of taxpayer relief in 1997 examined the relationship between CGT shocks and stock returns (Dai, Maydew, Shackelford, & Zhang). Their empirical analyses showed a significant increase in average stock prices during the week following the announcement of the CGT cut due to the dominance of the

capitalization effect (an increase in demand) over the lock-in effect (an increase in supply). However, their results also demonstrated the later dominance of the lock-in effect, implying an ambiguous net effect on pricing. Theoretically, however, as they concluded with the support of the empirical evidence, an increase in both demand and supply would result in a net increase in the average trading volume of stocks. However, although trading volume-based factors were assumed to be significant determinants of stock returns in the past (Haugen & Baker, 1996), establishing a direct and consistent relationship remained a challenge. Hanlon and Heitzman (2010) conducted one of the most comprehensive reviews on tax research, including their effect on stock prices, and demonstrated the failure of various approaches to catch the traces of the effects of taxes on stock returns. As also emphasized by Hanlon and Heitzman as a possible explanation for the continuing ambiguity on the subject, Fama and French (1998) theoretically justified the inability to generate isolated information of such traces due to various reasons such as high information cost for tax effects (i.e., their effect -if it exists- is very likely grasped by the other factors, and therefore not observable).

Another extension of CAPM was the introduction of non-marketable assets to the model by Mayers in 1973. Although traditional CAPM only accounted for marketable assets, Mayers extended CAPM to include “non-marketable” (i.e., perfectly illiquid) assets. In addition to those relaxations of strict assumptions, Merton (1973) developed I-CAPM, in which any change in the investment opportunity set affects both consumption and future asset return. This work was seminal given the fact that the single-period CAPM could not be used with multi-period settings (as investors’ given opportunity sets and preferences are

time-varying). This opened the door for researchers to explore new factors that could explain time-varying preferences, thus catalyzing the development of well-defined multi-factor intertemporal models, such as the three-factor model of Campbell (1996). According to Ince (2022), Campbell's model is an integration of I-CAPM with augmented factors proxying returns of human capital and market risk.

On the other hand, a vastly different perspective on the risk-return relationship was offered by the APT (Ross, 1976). Along with its other substantial differences to CAPM (e.g., relative pricing), APT provided a strong theoretical essence for allowing many factors to influence stock prices (and not just the market). Nevertheless, it did not specify those factors (as discussed in Chapter 1). Shanken (1982) strongly criticized APT, suggesting that it is not empirically testable, referring to its fundamental shortcomings. For instance, he argues that simply “repackaging” the subsets could manipulate the factor analyses. Despite Dybvig and Ross (1985) responded Shanken's claims with an emphasis on the testability of equilibrium-APT models, Shanken (1985) claimed equilibrium-APT models to be reinterpretations of Multi-beta CAPMs with proxied assumptions (e.g., well-diversified market portfolios). Nonetheless, without denying its limitations, Fama (1991) admired the APT for verifying the existence of additional factors. As discussed in Chapter 1, the multi-factor models under the Fama-French framework were developed cumulatively from 1993 (FF3) to 2018 (momentum-augmented FF5).

In parallel with the development of the Fama-French framework, an alternative, accounting-based methodology to explain expected stock returns has also been established in recent decades as a result of cumulative research. An important

contribution was in the critique of FF3, emphasizing that the earnings-to-price ratio is missing from the model (Penman, Reggiani, Richardson & Tuna, 2018). However, it should also be noted that a factor of profitability (RMW, i.e., Robust-Minus-Weak) was already integrated in FF5 in 2015 by Fama and French, as discussed in Chapter 1. Similarly, the q-factor model also typically includes ROE (Return-on-Equity) as an alternative factor of profitability (Hou, Xue, & Zhang, 2014). In fact, as the earnings-to-price ratio can be accurately approximated by the multiplication of the book-to-price ratio and ROE, the earnings-to-price ratio is -indirectly- included in such models (Penman & Zhang, 2021). More recently, an accounting-based asset pricing model has been developed, which is a two-factor extension of I-CAPM, augmented with a complex variable based on various balance sheet measures (Penman & Zhu, 2022).

Despite the development of newer and more accurate asset pricing models, additional return predictors and persistent anomalies are yet to be discovered. For instance, Bali, Cakici, and Whitelaw (2011) examined the impact of extremely positive returns on stock valuations using the FFC as the benchmark model and found that there is an inverse relationship between anticipated risk-adjusted stock returns and the greatest daily return over the past month (MAX). Hence, they showed that stocks with higher maximum daily returns had lower risk-adjusted stock returns, and they used the terminology of “lottery-like” to address the abnormal characteristics of such stocks. In a more recent study, Ince and Ozsoylev (2020) extended Bali et al.’s work by introducing systematic and unsystematic (i.e., idiosyncratic) extreme daily returns (SMAX and IMAX, respectively) for the past month. Their analyses have shown that high-IMAX portfolios generate significantly

high four-factor alphas (using FFC), contrary to SMAX. In support of various other analyses, their Fama-Macbeth (1973) regression results also associated significant (insignificant) betas for IMAX (SMAX) when tested against other return predictors. As a result of such empirically robust analyses, they have concluded that the lottery-like behaviors proxied by MAX are almost entirely unsystematic (i.e., the effect vastly comes from IMAX and not the market). They provided behavioralist explanations (such as investor sentiment) to address the proven idiosyncrasy.

Czapkiewicz et al. (2023) investigated the low-risk anomaly and its underlying nature and sources in emerging markets and found a negative correlation between idiosyncratic volatility and returns in European emerging markets, which was primarily driven by underpriced stocks. The effect is further amplified by high turnover and liquidity. Their study suggests that the idiosyncratic risk anomaly can be explained by the illiquidity-enhanced three-factor model, thereby highlighting the importance of considering market-specific dynamics when examining anomalies. It should also be noted that there is ongoing criticism of such empirical practices to discover such anomalies and return predictors (mainly centered on the denial of the reproducibility of the results), as addressed by Chen and Zimmermann (2022). Nevertheless, Chen and Zimmerman (2022) analyzed 161 predictors that are claimed initially to be significant by their “inventors” and found that 98% (which they concluded to be “nearly 100%”) generate statistically significant intercepts for long-short portfolios. This essentially means that such false denials cannot serve as a means to devalue (or distrust) the entire literature that we attempt to merely summarize in this chapter.

This extensive body of research demonstrates the continuous efforts to identify and understand the factors that drive stock market performance. These studies collectively emphasize the importance of fundamental information in analyzing stock returns. The observed phenomena and proposed explanations warrant further research to fully understand the underlying mechanisms and their implications for asset pricing models and investment strategies.

CHAPTER 3

RESEARCH QUESTIONS, AIMS AND OBJECTIVES

The main purpose of this research study is to examine the implications of incorporating balance sheet metrics using portfolio-level analyses and Fama-MacBeth regressions. Specifically, we aim to examine whether anomalies persist in expected returns even after accounting for these metrics. The following objectives will guide our research:

- **Assess the Impact of Balance Sheet Indicators on Stock Returns:** The first objective is to determine the influence of three key balance sheet indicators (i.e., CDA, WCA, LTDA) on stock returns across a diverse cross-section of stocks. By analyzing the relationship between these indicators and anticipated returns, we aim to provide insights into the relevance of incorporating balance sheet metrics in asset pricing models.
- **Examine the Relationship between Balance Sheet Conservativity and Returns:** We investigate whether companies with balance sheet conservativity generate significantly higher returns compared to those with less conservative financial policies. This analysis aims to evaluate the impact of prudent financial practices on investment outcomes to gain insights into the potential benefits of maintaining a conservative balance sheet.
- **Investigate Stock Market Mispricing Related to Balance Sheet Measures:** We explore whether there is empirical evidence of stock market mispricing associated with balance sheet measures. By identifying any disparities or

inefficiencies in stock pricing attributed to balance sheet information, we seek to contribute to the understanding of market valuation accuracy and potential opportunities for abnormal returns.

By analyzing the significance of balance sheet indicators, namely cash/asset, working capital, and long-term debt/asset, we aim to provide a deeper understanding of how these metrics influence stock returns in various stock market scenarios. Three research questions will guide this study to fulfill its objectives:

Q1) How do balance sheet indicators influence equity returns across a range of stocks?

This question delves into the relationship between the aforementioned three balance sheet measurements and stock returns. The objective is to ascertain whether these measures are priced accurately in the market and have a discernible impact on equity returns.

Q2) Do corporations with conservative balance sheets generate significantly higher returns?

This question explores the connection between balance sheet conservativity and stock returns. Specifically, we aim to determine whether companies that adhere to conservative financial policies tend to achieve higher returns compared to their counterparts with less conservative balance sheets.

Q3) Is there any evidence of mispricing in the stock market concerning balance sheet measures?

This question seeks to identify disparities or inefficiencies in stock pricing that can be attributed to balance sheet information. By investigating potential mispricing opportunities, we hope to shed light on the accuracy of stock market valuations based on balance sheet indicators.

The first question addresses the relationship between balance-sheet indicators and stock returns across a range of stocks. By exploring this connection, the research aims to ascertain whether these indicators are accurately priced in the market and whether they have a discernible impact on stock returns. Understanding the extent to which balance sheet metrics affect stock returns can provide valuable insights for investors and financial analysts.

The second question focuses on the relationship between balance sheet conservativity and stock returns. By examining whether companies with conservative financial policies generate significantly higher returns, the research aims to explore the potential benefits of maintaining a conservative balance sheet. Understanding the impact of balance-sheet conservativity on stock returns can provide valuable insights for companies and investors alike, aiding in financial decision-making and portfolio management strategies.

The third question investigates whether there is evidence of mispricing in the stock market related to balance sheet measures. By identifying potential disparities or

inefficiencies in stock pricing attributed to balance sheet information, the study seeks to shed light on the accuracy of stock market valuations. Uncovering any mispricing opportunities can have significant implications for investors seeking to capitalize on market inefficiencies.

In light of these research questions, this study intends to:

1. Document that the balance sheet measures of interest (i.e., CDA, WCA, and LTDA) are priced in the cross-section of stock returns.
2. Introduce a composite index based on these measures and test its significance against known risk factors in the literature.
3. Discuss the possibility of risk or mispricing explanations for the observed relationship.

The findings of the analyses will help enhance the understanding of financial risk, market efficiency, and the influence of financial practices on investment outcomes.

The practical implications of this research include improving investment decision-making processes, portfolio management strategies, and financial policy formulation for both investors and companies.

CHAPTER 4

DATA AND METHODOLOGY

The dataset utilized in this study comprises monthly adjusted closing stock prices of 83,436 corporations listed on various stock exchanges, including the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ), American Stock Exchange (AMEX). The data span from January 1970 to December 2020 were accessed using the Wharton Research Data Service (WRDS). Monthly returns were taken from CRSP (The Center for Research in Security Prices), while balance sheet measures were measured using accounting information from the CRSP/Compustat merged database. Likewise, monthly data of all seven factors for our time span were accessible (and thus obtained) through WRDS under the “Fama & French Portfolios & Factors” data vendor. Inspired by a recent study’s methodology (Ince, 2022a), stocks that are traded under \$5 were excluded from the data to dismiss the effect of micro-capacity (and possibly illiquid) firms. Portfolio-level analyses and Fama-MacBeth regressions were employed for this dataset so as to achieve the research objectives described in Chapter 3. On the other hand, return predictors that were utilized in the Fama-MacBeth regressions and descriptive statistics were either calculated using existing data or obtained from various open databases, which will be specified and addressed explicitly with their definitions within the respective subsections.

This chapter first introduces the balance sheet measures of interest (Section 4.1), which are utilized in both methods. Section 4.2 consists of the derivation of their

composite, namely Balance Sheet Conservativity (BLC), which will also be used in portfolio-level analyses. Lastly, Section 4.3 examines the details of the empirical framework of both techniques and how they are used in our study.

4.1 Balance Sheet Measures

- **Cash-to-Assets (CDA)**

The cash-to-assets ratio (i.e., cash divided by assets) is a crucial financial metric that evaluates the portion of a company's total assets represented by cash. This ratio is an essential measure of liquidity and financial prudence presented on a company's balance sheet as it reveals the percentage of total assets held in the form of cash. A high cash-to-assets ratio demonstrates that the corporation has high liquidity and can easily satisfy its short-term obligations. Additionally, it could suggest a cautious financial strategy or a scarcity of investment prospects. In contrast, a lower cash-to-assets ratio shows that a corporation has a lesser ratio of cash holdings to its total assets. This can mean that the business has made significant investments in other assets such as inventories, real estate, machinery, and equipment. If the company encounters financial difficulties or cash flow issues, a smaller ratio can suggest a larger risk of not being able to satisfy short-term obligations.

The cash-to-assets ratio is important in the context of balance sheet conservativity and the cross-section of stock returns for numerous reasons, as listed below:

- **Liquidity Risk:** A higher cash-to-assets ratio indicates that a company possesses a greater ability to settle its short-term debts and sustain its operations. It reveals the company's liquidity situation and its ability to survive difficult financial times or unanticipated catastrophes.
- **Financial Stability:** Businesses with a higher cash-to-assets ratio are typically seen as conservative and financially stable. They have a “safety net” of cash on hand that they can use to weather economic downturns, invest in business expansion prospects, or pay unexpected bills. This stability may help the market see the company as resilient, which may positively impact stock returns.
- **Investment Opportunities:** The cash-to-assets ratio also influences a company's capacity to capitalize on investment opportunities. A firm's ability to make strategic acquisitions, fund R&D initiatives, or incur capital expenditures is facilitated by having greater cash reserves. Because investors may interpret this ability to undertake growth projects as a sign of possible future value creation, it can have a beneficial impact on stock returns.
- **Market Sentiment and Investor Perception:** Investor sentiment and perception of a company can be impacted by the cash-to-assets ratio. Investors may favor a company with a larger cash position since it denotes financial responsibility, less risk, and the possibility of dividend payments or share repurchases. Such a positive attitude can attract investors and boost stock gains.

- **Working Capital-to-Assets (WCA)**

Working capital represents the surplus of a company's current assets over its current liabilities. It gauges the company's capacity to fulfill its short-term obligations with its liquid assets. A positive working capital signifies that the company possesses ample liquid assets to settle short-term debts and sustain internal growth, reflecting favorable short-term financial well-being. Conversely, negative working capital implies that a company's assets are being utilized inefficiently, which may lead to a liquidity crisis and the need to borrow additional funds or raise capital. However, even if a company has substantial investments in fixed assets, its financial and operational stability may be threatened if its liabilities become due, resulting in late payments to creditors, borrowing, and a lower corporate credit rating. Therefore, the working capital-to-assets ratio (i.e., working capital divided by total assets) is a crucial element of a balance sheet. Below are some possible justifications for WCA:

- **Operational Effectiveness:** WCA serves as a measure of a company's ability to manage its short-term assets and liabilities effectively. Because it can efficiently finance its ongoing business activities and pay its short-term debts, a company with a well-managed working capital position exhibits operational efficiency.
- **Investment and Growth:** WCA is also necessary to enable prospects for investment and growth. A business that has sufficient working capital can finance expansion plans, make R&D investments, and benefit from strategic initiatives.

➤ **Financial Flexibility:** A company's financial flexibility is boosted by a well-managed working capital position, which makes it possible to negotiate good credit conditions, pay bills on time, and take advantage of sales and other opportunities in the marketplace. This adaptability may improve the company's competitive position and possibly affect stock returns as investors take notice of the company's sound financial management.

- **Long-Term Debt to Assets (LTDA)**

The LTDA ratio is a financial metric that examines a company's leverage and solvency by dividing its long-term debt by its total assets. Long-term debt pertains to the portion of a company's liabilities that will mature in more than a year, while total assets encompass both current assets (e.g., cash, inventory, and accounts receivable) and non-current assets (e.g., property, plant, and equipment). It provides insights into how much a firm relies on borrowing to fund its operations and investing activities. A greater ratio indicates a higher level of leverage, demonstrating that a significant portion of the company's assets is funded through long-term debt. This ratio sheds light on a company's leverage and capacity to fulfill its long-term obligations.

Several reasons can explain the significance of the long-term debt-to-assets ratio in balance sheet conservativity and the cross-section of stock returns:

- **Financial Stability:** A company is more likely to rely less on debt financing and is considered financially stable if it has a low long-term debt-to-assets ratio. This ratio reflects the company's enhanced capacity to fulfill its long-term debt obligations, thereby reducing the risk of default and financial trouble.
- **Risk and Return Tradeoff:** The risk profile of a company is influenced by its LTDA ratio. Higher levels of long-term debt indicate increased financial risk as the company has higher interest obligations and may face challenges in meeting debt payments. Investors usually anticipate higher returns to offset the added risk that accompanies companies with substantial long-term debt.
- **Creditworthiness:** The LTDA ratio holds significant importance as a metric for assessing the creditworthiness of a company. A higher ratio can negatively impact a company's credit rating, making it more expensive for it to raise capital through debt issuance. Conversely, a lower ratio enhances a company's creditworthiness, leading to better financing terms and potential stock price appreciation.

4.2 Balance Sheet Conservativity (BLC)

The balance sheet conservativity factor is derived by combining three key balance sheet indicators: the cash-to-assets ratio, working capital, and long-term debt, as explained previously. This factor serves as a measure of the conservativity or prudence exhibited by a company in managing its financial resources and obligations. As such, its rank is derived by linearly aggregating three fundamental

balance sheet indicators: cash-to-assets ratio, working capital, and long-term debt.

The equation for the rank of the balance sheet conservativity factor is as follows:

$$rank(BLC) = rank(CDA) + rank(WCA) + rank(-LTDA)$$

Where,

- BLC = Balance sheet conservativity factor
- CDA = Cash-to-assets ratio (cash divided by total assets)
- WCA = Working capital to assets ratio (i.e., working capital divided by total assets)
- LTDA = Long-term debt-to-assets ratio (i.e., long-term debt divided by total assets)

This methodology enables a comprehensive evaluation of the performance and influence of the balance sheet conservativity factor on both value-weighted (VW) and equal-weighted (EW) portfolios. The returns for all portfolio sets are calculated on a monthly basis, and portfolio rebalancing takes place annually to maintain the desired allocation.

Lastly, it should also be noted that this study's definition of this newly-established character of "balance sheet conservativity" should not be associated with some of the linguistically similar terms of "accounting conservatism", or "balance sheet conservatism", that were commonly used by accounting professionals. Both terms correspond to vastly different concepts related to financial reporting that are vastly

irrelevant to the scope of this research and excessively dissimilar to the BLC-characteristic.

4.3 Empirical Framework

4.3.1 Extension of the Fama-French Five-Factor Model

The FF5, which expands on the three-factor model developed by Fama and French in 1993, incorporates five factors that capture different sources of systematic risk in stock returns: market risk (captured by the market return), size (measured by the difference in returns between small and large companies), value (measured by the difference in returns between high book-to-market and low book-to-market companies), profitability (measured by the difference in returns between high and low profitability companies), and investment (measured by the difference in returns between high and low investment companies).

The equation for the Fama-French five-factor model is as follows:

$$R_{i(t+1)} - R_{f(t+1)} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + r_iRMV_t + u_iCMA_t + \epsilon_{it}$$

Where:

- $(R_i - R_f)$ is the excess return of stock i over the risk-free rate (R_f).

- The excess return of the market portfolio ($R_{mt} - R_{ft}$) captures the systematic risk associated with overall market movements, i.e., Market Risk.
- The factor loadings ($\beta_i, s_i, h_i, r_i, u_i$) measure the sensitivity of the stock's returns to the respective factors. Positive loadings indicate that the stock tends to have higher returns when the factor is performing well, while negative loadings suggest the opposite.
- The intercept term (α_i) represents the stock-specific intercept or alpha, which captures the stock's abnormal return not explained by the factors, i.e., the abnormal return of the stock that is not explained by the factors in the model. A positive alpha suggests that the stock outperforms the model's predictions, while a negative alpha suggests underperformance.
- ϵ_{it} represents the stock-specific error term, which proxies for the idiosyncratic risk.

Although our study uses FF5 as its basis, we employ its commonly-used extension with two additional factors. The supplementary factors incorporated in the present study can be mathematically represented by the following equation:

$$R_{p(t+1)} - R_{f(t+1)} = \alpha_p + \lambda_1 (R_{mt} - R_{ft}) + \lambda_2 SMB_t + \lambda_3 HML_t + \lambda_4 RMW_t \\ + \lambda_5 CMA_t + \lambda_6 UMD_t + \lambda_7 LIQ_t + \epsilon_{pt}$$

Where:

- $(R_p - R_f)$ represents the constructed portfolio's excess return over the risk-free rate. Note that R_f will be proxied by returns of 30-day T-bill investments throughout this study.
- UMD: The momentum factor, as previously discussed in Chapter 1, was already self-augmented to FF5 by Fama and French in 2018.
- LIQ: The liquidity factor of Pastor and Stambaugh (2003). Integration of LIQ as a seventh factor to the momentum-augmented FF5 was also successfully practiced before in seminal works (e.g., Bali, Brown & Tang, 2017). It should also be clarified that LIQ represents the “traded” liquidity factor, and not the “non-traded” alternative that was endorsed in the same paper (Pastor & Stambaugh, 2003). While both can be useful under different circumstances, their “inventors” recommended using the traded version for estimating multi-factor alphas (Pastor & Stambaugh, 2019).
- The intercept term (α_p) represents the risk-adjusted excess returns of the *portfolios*, rather than the individual stocks.
- Likewise, ϵ_{pt} represents the error term that proxies the idiosyncratic risk for the constructed portfolio.

4.3.2 Portfolio Analyses and Fama-MacBeth Regressions

As discussed at the beginning of the chapter, the current study employs two different methods to achieve its research outcomes: portfolio-level analyses and Fama-Macbeth regressions. Portfolio-level analyses entail categorizing stocks into distinct groups based on a certain balance sheet variable and then analyzing the

performance of these groupings. It comprises dividing a group of securities into various portfolios or groups based on the values of a particular variable, such as cash/asset, working capital/asset, and long-term debt/asset, as explored in the current study. The stocks are typically ranked from low to high based on the chosen attribute and then divided into portfolios, with each portfolio owning an equal number of stocks. The main goal of these portfolio sorts is to test the statistical significance of the seven-factor alphas (demonstrated as α_p 's in the previous subsection) for the High-Low Difference Portfolios. Positively significant alpha scores will favor an investment strategy for buying the highest and shorting the lowest portfolios, as that would associate excessive returns associated with higher ratios of these balance sheet metrics. Descriptive statistics will also be utilized to explain the characteristics of the univariately constructed portfolios for CDA, WCA, LTDA, and BLC.

Additionally, Fama and MacBeth's (1973) two-step regression method is utilized to test the capability of the balance sheet measures to generate isolated risk premiums (i.e., λ_{CDA} , λ_{WCA} , λ_{LTDA}), when tested against well-known return predictors.

Obviously, λ_{BLC} cannot be measured with this method because of its discreteness due to its rank-based construction. The error terms derived from the cross-sectional regressions are likely to exhibit autocorrelation and heteroskedasticity. In order to address this issue, Newey-West heteroskedasticity and autocorrelation corrected (HAC) standard errors are employed to calculate the t-statistics, using six lags. An absolute value of the Newey-West adjusted t-statistic which reported greater than 1.96 will be associated with statistical significance (under 95% confidence interval) throughout the analyses.

To that end, a monthly panel of stocks of 83,436 corporations from January 1970 to December 2020, as discussed in the previous section, is considered for the procedure. The endogenous variable should be the excess return of the asset (i.e., the return minus the risk-free rate), and the exogenous variables can include market returns and other relevant factors. The estimated coefficients (betas) represent the sensitivity of the asset's returns to the exogenous variables that are derived in the first step by cross-sectional regressions. The second step involves taking the time-series average of the betas obtained in the previous step, which will result in the derivation of respective risk premiums (λ_i). The following econometric specification is used for the regression:

$$\begin{aligned}
 R_{i,t+1} = & \lambda_0 + \lambda_1 * CDA_{i,t} + \lambda_2 * BETA_{i,t} + \lambda_3 * SIZE_{i,t} + \lambda_4 * BM_{i,t} + \lambda_5 * REV_{i,t} \\
 & + \lambda_6 * MOM_{i,t} + \lambda_7 * ROE_{i,t} + \lambda_8 * VOL_{i,t} + \lambda_9 * ILLIQ_{i,t} + \lambda_{10} * MAX_{i,t} \\
 & + \lambda_{11} * AG_{i,t} + \epsilon_{i,t}
 \end{aligned}$$

Where,

- R_i = Excess return of the asset (i.e., the return minus the risk-free rate)
- CDA can be replaced by other measures of interest (namely WCA, LTDA).
- BM = Book-to-market (BM) is calculated as the natural logarithm of the ratio of the book value of a firm to its size.
- REV = Defined and calculated as the excess return generated over the past month.

- SIZE = Calculated as the stock's number of shares outstanding multiplied by their price per share.
- ROE = Return on Equity (ROE) is a widely-used profitability measure, as previously defined in Chapter 2. Monthly data related to this measure was obtained from the Hou-Xue-Zhang q-factors data library (Hou, Xue, & Zhang, 2022).

The following return predictors were directly attained from the Open Source Asset Pricing Database (Chen & Zimmermann, 2022):

- BETA and MAX, which were already introduced in the prior chapters.
- MOM = Momentum factor, which refers to the cumulative return of a stock over the last 11 months (Jegadeesh & Titman, 1993).
- IVOL = Idiosyncratic Volatility measure (Ang, Hodrick, Xing, & Zhang, 2006)
- ILLIQ = Illiquidity measure of Amihud (2002)
- AG = Annual growth of total assets (Cooper, Gulen, & Schill, 2008)

CHAPTER 5

EMPIRICAL RESULTS AND DISCUSSION

This chapter focuses on examining and discussing the empirical results regarding the firm-level cross-sectional relationship between balance sheet measures of conservativity and stock returns. The analysis is conducted in several sections. Sections 5.1 and 5.2 involve univariate and bivariate portfolio-level analyses, respectively. Section 5.3 presents a summary of descriptive statistics for each balance sheet measure and composite factor. Section 5.4 includes the Fama-Macbeth (1973) regression outcomes. Lastly, Section 5.5 discusses the societal impact of our study. Each section includes reporting and the interpretation of the empirical results alongside the relative theoretical discussions.

5.1 Univariate Portfolio-Level Analyses

The presented tables exhibit quintile portfolios that are formed on a monthly basis by sorting stocks according to their rank of each balance sheet measure. Quintile Portfolios 1 and 5 include stocks with the lowest and highest scores, respectively. The tables display the average excess returns (RET-RF) and alphas (α_7) for each portfolio, both in EW and VW terms. The last rows display the average monthly return and alpha differences between the extreme portfolios. Hence, the α_7 scores of the last rows are crucially important as they also stand as a test for a possible investment strategy on such measures (i.e., buying the highest-scored portfolio stocks and shorting the lowest).

5.1.1 Cash-to-Assets (CDA)

As **Table 1** shows, the alphas (α_7) for the high-low difference of both the EW and VW portfolios based on the CDA scores are significant with immense Newey-West t-statistics (4.44 and 7.16, respectively). For the VW case, the results indicate an investment strategy of acquiring stocks of companies that hold more cash (Portfolio 5) and shorting the ones that hold less (Portfolio 1) would generate more than 8% excess returns than investing in a risk-free asset (i.e., 30-day T-bill).

Table 1: Univariate Portfolio Analysis of Stocks Sorted by CDA

The table displays the average excess returns (RET-RF) and risk-adjusted returns (α_7) relative to the seven-factor model. The last row of the table shows the differences in average monthly returns and alphas between the highest and lowest portfolios based on their CDA scores. Newey-West (1987) adjusted t-statistics using six lags reported in parentheses. The sample period is from January 1970 to December 2020.

Quintile	EQUAL-WEIGHTED		VALUE-WEIGHTED	
	RET-RF	α_7	RET-RF	α_7
Low Portfolio	%0.62 (2.95)	-%0.13 (-2.41)	%0.47 (2.61)	-%0.24 (-5.05)
2	%0.68 (3.01)	-%0.13 (-2.44)	%0.48 (2.43)	-%0.23 (-4.22)
3	%0.74 (3.12)	-%0.10 (-1.86)	%0.68 (3.52)	-%0.01 (-0.19)
4	%0.81 (3.14)	%0.10 (2.75)	%0.69 (3.17)	%0.10 (1.84)
High Portfolio	%0.70 (2.58)	%0.26 (4.64)	%0.80 (3.13)	%0.48 (6.29)
High-Low difference	%0.09 (0.53)	%0.40 (4.44)	%0.33 (1.95)	%0.72 (7.16)

5.1.2 Working Capital-to-Assets (WCA)

Similarly to the first measure, **Table 2** shows that the alphas (α_7) for the high-low difference of both the EW and VW portfolios based on the WCA scores are

significant given their Newey-West t-statistics (2.97 and 3.73, respectively). Again, this effectively corresponds to a significantly better outcome for a high-low strategy than a risk-free investment. (For the VW case, the numbers indicate more than 6% annual excess returns.)

Table 2: Univariate Portfolio Analysis of Stocks Sorted by WCA

The table displays the average excess returns (RET-RF) and risk-adjusted excess returns (α_7) relative to the seven-factor model. The last row of the table shows the differences in average monthly returns and alphas between the highest and lowest quintile portfolios based on their WCA scores. Newey-West (1987) adjusted t-statistics using six lags are reported in parentheses. The sample period is from January 1970 to December 2020.

Quintile	EQUAL-WEIGHTED		VALUE-WEIGHTED	
	RET-RF	α_7	RET-RF	α_7
Low Portfolio	%0.66 (3.21)	-%0.09 (-1.45)	%0.59 (3.68)	-%0.08 (-1.51)
2	%0.73 (3.10)	-%0.06 (-1.09)	%0.64 (3.47)	%0.00 (0.04)
3	%0.79 (3.22)	%0.02 (0.50)	%0.61 (2.85)	%0.08 (1.22)
4	%0.78 (3.01)	%0.10 (2.07)	%0.73 (3.12)	%0.37 (4.33)
High Portfolio	%0.63 (2.22)	%0.21 (3.52)	%0.69 (2.30)	%0.43 (4.24)
High-Low difference	-%0.03 (-0.15)	%0.30 (2.97)	%0.10 (0.45)	%0.51 (3.73)

5.1.3 Long-Term Debt-to-Assets (LTDA)

As **Table 3** shows, the alphas (α_7) for the high-low difference of both the EW and VW portfolios based on LTDA scores are negatively significant, given their Newey-West t-statistics (-4.01 and -3.82, respectively). This inverse relationship points to the significance of a similar (but reverse) strategy to the first two factors; that is, the acquisition of Portfolio 1 (low) and selling of Portfolio 5 (high). In this case, as the analysis shows, the investor would again be significantly better off, exploiting nearly 6% excess returns.

Table 3: Univariate Portfolio Analysis of Stocks Sorted by LTDA

The table displays the average excess returns (RET-RF) and risk-adjusted excess returns (α_7) relative to the seven-factor model. The last row of the table shows the differences in average monthly returns and alphas between the highest and lowest quintile portfolios, based on their scores on LTDA. Newey-West (1987) adjusted t-statistics using six lags are reported in parentheses. The sample period is from January 1970 to December 2020.

Quintile	EQUAL-WEIGHTED		VALUE-WEIGHTED	
	RET-RF	α_7	RET-RF	α_7
Low Portfolio	%0.70 (2.97)	%0.20 (4.44)	%0.68 (2.80)	%0.40 (4.15)
2	%0.69 (2.89)	%0.05 (0.96)	%0.60 (2.96)	%0.05 (0.93)
3	%0.79 (3.46)	%0.03 (0.63)	%0.64 (3.27)	%0.00 (0.01)
4	%0.75 (3.30)	-%0.07 (-1.43)	%0.64 (3.47)	-%0.13 (-2.38)
High Portfolio	%0.67 (2.78)	-%0.13 (-2.10)	%0.56 (2.97)	-%0.09 (-1.36)
High-Low difference	-%0.03 (-0.30)	-%0.33 (-4.01)	-%0.12 (-0.82)	-%0.49 (-3.82)

5.1.4 Balance Sheet Conservativity Factor (BLC)

Table 4 explores the relationship between the balance sheet conservativity factor (BLC) and stock performance. The overall results indicate significant seven-factor alphas for the High-Low portfolios, with Newey-West t-statistics of 3.81 and 4.38, respectively for the EW and VW portfolio analyses. For the VW case, the high-low portfolio generates more than 7% risk-adjusted annual excess return, which could be emphasized in favor of a more comprehensive investment strategy: invest in stocks of firms that have more conservative balance sheets (i.e., holding more cash and working capital and less long-term debt), and short-sell the assets of companies that lack such characteristics.

Table 4: Univariate Portfolio Analysis of Stocks Sorted by BLC

The table displays the average excess returns (RET-RF) and risk-adjusted excess returns (α_7) relative to the seven-factor model. The last row of the table shows the differences in average monthly returns and alphas between the highest quintile portfolios, based on their scores on BLC. Newey-West (1987) adjusted t-statistics using six lags are reported in parentheses. The sample period is from January 1970 to December 2020.

Quintile	EQUAL-WEIGHTED		VALUE-WEIGHTED	
	RET-RF	α_7	RET-RF	α_7
Low Portfolio	%0.65 (2.96)	-%0.16 (-2.41)	%0.57 (3.35)	-%0.16 (-2.79)
2	%0.68 (2.81)	-%0.16 (-2.77)	%0.61 (3.30)	-%0.10 (-2.21)
3	%0.76 (3.07)	%0.01 (0.26)	%0.64 (3.19)	%0.04 (0.67)
4	%0.76 (2.95)	%0.17 (3.58)	%0.73 (2.97)	%0.36 (4.63)
High Portfolio	%0.68 (2.37)	%0.25 (4.00)	%0.69 (2.40)	%0.46 (4.36)
High-Low difference	%0.04 (0.21)	%0.42 (3.81)	%0.12 (0.57)	%0.62 (4.38)

In summary, according to the results of the univariate sorts, the three balance sheet measures (CDA, WCA, and LTDA) and their composite factor (BLC) appear to have significant influences on portfolio performances. The persistence of the statistical significance of high-low difference when accounting for different factors under the logical characteristic of “balance sheet conservativity” opens the door to a more comprehensive analysis of stock performances and characteristics of different corporations.

5.2 Bivariate Portfolio-Level Analyses

In addition to the univariate portfolio-level analysis based on BLC scores (Section 5.1.4), this section utilizes bivariate sorting with the consideration of three key variables of the composite factor: size, illiquidity, and mispricing.

It should be noted that the mispricing will be measured using the MISP Scores (Stambaugh, Yu, & Yuan, 2015). The data for MISP scores were obtained from Robert F. Stambaugh's online data library. Following their methodology, MISP is assigned to each stock, ranging from 0 to 100, which is determined by calculating its percentile rank for 11 different anomalies. Stocks with higher (lower) MISP values are considered to be relatively overpriced (underpriced). As it is a relative measure, Stambaugh et al. did not endorse an "ideal" MISP score. However, average MISP scores close to 50 are deemed to be "fairly valued" (Cao J., Titman, Zhan & Zhang, 2019). For a large sample of US stocks, the mean (median) MISP score has been found to be 49.4 (48.9) with a standard deviation (std. dev) close to 13. (Cao J., Titman, Zhan & Zhang, 2022). Approximately identical results (i.e., mean=49.4, median=48.7, and a std. dev approaching 13) have been found from another large-sample study, pooling more than 300,000 observations (Cao Z., Chelikani, Kilic & Wang, 2022).

Although the focus will again be on the seven-factor alphas, an average for the median mispricing scores of each portfolio has also been embedded in size and illiquidity tables to demonstrate the mispricing (MISP) patterns. An important note for the MISP measure is that, as the data are only available until December 2016, it could not be employed in the Fama-Macbeth regressions without reducing the sample size (which ends at the end of 2020). Likewise, any considerations regarding the mean-median MISP score patterns of ranked portfolios should assume that the inclusion of MISP scores for the last four years' stocks in the respective portfolios would not significantly affect the patterns of the previous 46 years' bivariate sorted

portfolios (as those portfolios were constructed using 50 years' worth of data). Nonetheless, such a generalization would not be irrational, given that the MISP accounts for various factors of stock performances, and the missing data corresponds to a very small percentage of observations. Such a drastic deviation from typical market behaviors to an extent to change the patterns of remaining MISP scores data in favor (or expense) of different portfolios would be highly unrealistic and can safely be dismissed in the mean-median analyses in Sections 5.2.1 and 5.2.2. However, a sample adjustment was needed for Section 5.2.3. as MISP is the key variable.

5.2.1 Size

Table 5 presents the portfolio details derived from sorting variables along with their associated alphas. The initial column delineates the threshold values for the SIZE sorting variable, employed to classify stocks into distinct portfolios. The subsequent column establishes the thresholds for the balance sheet conservativity sorting criterion. In order to adjust for the size disparities, stocks are first segmented into low, medium, and high categories based on the 33rd and 67th percentiles. Within these defined portfolios, stocks are further distributed into quintiles predicated on their balance sheet conservativity. According to the results, sized portfolios tend to observe slightly less (more) overvaluation (undervaluation) than mid and low-sized ones. As the MISP factor is typically negatively correlated with SIZE (Cao Z. et al., 2022), this is not a surprising result. On the other hand, both the EW and VW portfolio analyses indicate significant risk-adjusted excess returns for the High-Low Difference portfolio. For the EW case, the corresponding Newey-West t-statistics of

seven-factor alphas for low, mid, and high portfolios are 3.22, 3.35, and 3.57, respectively. The results for VW portfolios indicate the respective numbers to be 3.45, 2.83, and 4.13.

Table 5: Bivariate Portfolio Analysis of Stocks on 5x3 Sorted Portfolios (Size)

Double-sorted equal-weighted and value-weighted portfolios are constructed and utilized using the seven-factor model. Stocks are first sorted based on their size, and then within each size-sorted portfolio, they are further sorted based on their balance sheet conservativity factor (BLC) ranks. The first two columns present the breakpoints or cut-off points determined by each of these factors. Average excess returns (RET-RF) and risk-adjusted excess returns (alphas) are reported alongside the respective parentheses containing the Newey-West (1987) adjusted t-statistics (using six lags). The sample period is from January 1970 to December 2020 (Except for MISF, which does not extend to the time period after December 2016).

SIZE	BLC Quintile	EQUAL-WEIGHTED		VALUE-WEIGHTED		$\mu(\text{median_misp})$	
		RET-RF	α_7	RET-RF	α_7		
LOW (BOTTOM 33%)	Low-BLC	0.0063 (2.29)	-0.0017 (-1.56)	0.0065 (2.35)	-0.0018 (-1.80)	50.3220	50.3201
	2	0.0076 (2.85)	-0.0005 (-0.54)	0.0078 (2.82)	-0.0008 (-0.89)	50.3111	
	3	0.0077 (2.86)	0.0003 (0.38)	0.0078 (2.78)	0.0000 (0.04)	50.3146	
	4	0.0075 (2.75)	0.0010 (1.31)	0.0073 (2.58)	0.0007 (0.82)	50.3183	
	High-BLC	0.0070 (2.45)	0.0022 (2.42)	0.0078 (2.61)	0.0030 (2.86)	50.3359	
	High-Low difference	0.0007 (0.42)	0.0039 (3.22)	0.0013 (0.70)	0.0048 (3.45)	0.0140	
MID (MIDDLE 34%)	Low-BLC	0.0069 (2.72)	-0.0022 (-3.08)	0.0071 (2.89)	-0.0021 (-2.89)	50.4004	50.3944
	2	0.0068 (2.57)	-0.0019 (-3.07)	0.0069 (2.62)	-0.0018 (-2.99)	50.3866	
	3	0.0076 (2.80)	-0.0003 (-0.54)	0.0079 (2.94)	0.0000 (0.06)	50.4006	
	4	0.0075 (2.71)	0.0020 (2.28)	0.0075 (2.73)	0.0021 (2.47)	50.3813	
	High-BLC	0.0066 (2.15)	0.0021 (2.29)	0.0062 (1.99)	0.0018 (1.77)	50.4032	
	High-Low difference	-0.0003 (-0.14)	0.0043 (3.35)	-0.0009 (-0.45)	0.0039 (2.83)	0.0028	
HIGH (TOP 33%)	Low-BLC	0.0063 (3.42)	-0.0009 (-1.23)	0.0054 (3.26)	-0.0013 (-1.86)	46.0899	46.0818
	2	0.0069 (3.24)	-0.0016 (-2.22)	0.0055 (3.09)	-0.0018 (-3.37)	46.0978	
	3	0.0066 (3.00)	-0.0008 (-1.66)	0.0065 (3.38)	-0.0004 (-0.91)	46.0730	
	4	0.0071 (3.01)	0.0015 (3.03)	0.0064 (2.91)	0.0021 (3.02)	46.0666	
	High-BLC	0.0069 (2.54)	0.0034 (4.53)	0.0070 (2.69)	0.0049 (4.76)	46.0801	
	High-Low difference	0.0007 (0.34)	0.0044 (3.57)	0.0016 (0.81)	0.0062 (4.13)	-0.0098	

Accordingly, the statistical significance of long-short (high-low) alphas in all cases indicates that BLC can be claimed as a significant indicator for the cross-section of stock returns, regardless of the size of the corresponding company.

5.2.2 Illiquidity

The stocks are first classified as low, medium, and high illiquidity portfolios based on percentiles and then classified as quintiles based on the balance sheet conservativity factor within each ranked portfolio in **Table 6**. Similar to the previous subsection, mean-median analyses regarding MISP are again in parallel with the usual patterns, as highly liquid assets are typically associated with lower MISP scores (Cao Z. et al., 2022). More importantly, the results clearly indicate that the seven-factor alphas remain significant for the High-Low Difference portfolio across all levels of illiquidity. The Newey-West adjusted t-statistics for low, mid, and high illiquidity portfolio alphas are respectively 3.52, 3.00, 2.59 for EW and 3.96, 2.28, 2.45 for VW. The Newey-West adjusted t-statistics for low, mid, and high liquidity portfolio alpha are 3.52, 3.00, and 2.59 for EW and 3.96, 2.28, and 2.45 for VW, respectively. Hence, in support of the previous portfolio-level analyses, BLC stands out as a pivotal determinant in the cross-sectional analysis of stock returns, independent of the associated company's liquidity levels.

Table 6: Bivariate Portfolio Analysis of Stocks on 5x3 Sorted Portfolios (Illiquidity)

Double-sorted equal-weighted and value-weighted portfolios are constructed and utilized using the seven-factor model. Stocks are first sorted based on their illiquidity scores (ILLIQ), and then within each illiquidity-sorted portfolio, they are further sorted based on the balance sheet conservativity factor (BLC). The first two columns present the breakpoints or cut-off points determined by each of these factors. Average excess returns (RET-RF) and risk-adjusted excess returns (alphas) are reported alongside the respective parentheses containing the Newey-West (1987) adjusted t-statistics (using six lags). The sample period is from January 1970 to December 2020 (Except for MISP, which does not extend to the time period after December 2016).

Table 6 (cont'd)

ILLIQ	BLC Quintile	EQUAL-WEIGHTED		VALUE-WEIGHTED		$\mu(\text{median_misp})$	
		RET-RF	α_7	RET-RF	α_7		
LOW (BOTTOM 33%)	Low-BLC	0.0058 (3.20)	-0.0012 (-1.52)	0.0056 (3.47)	-0.0010 (-1.44)	46.7575	4 6 . 7 7 3 2
	2	0.0063 (2.95)	-0.0017 (-2.45)	0.0055 (3.05)	-0.0016 (-2.78)	46.7907	
	3	0.0066 (2.96)	-0.0002 (-0.33)	0.0063 (3.30)	-0.0005 (-1.04)	46.7744	
	4	0.0066 (2.70)	0.0022 (3.32)	0.0068 (3.10)	0.0032 (4.03)	46.7972	
	High-BLC	0.0065 (2.30)	0.0036 (3.80)	0.0068 (2.62)	0.0046 (4.85)	46.7461	
	High-Low difference	0.0007 (0.33)	0.0048 (3.52)	0.0013 (0.66)	0.0056 (3.96)	-0.0114	
MID (MIDDLE 34%)	Low-BLC	0.0070 (2.82)	-0.0017 (-2.34)	0.0076 (3.31)	-0.0010 (-1.31)	50.1746	5 0 . 1 7 5 3
	2	0.0068 (2.60)	-0.0019 (-3.01)	0.0067 (2.73)	-0.0020 (-3.11)	50.1683	
	3	0.0071 (2.68)	-0.0008 (-1.71)	0.0076 (3.05)	-0.0006 (-1.10)	50.1727	
	4	0.0072 (2.69)	0.0010 (1.70)	0.0073 (2.93)	0.0013 (1.98)	50.1696	
	High-BLC	0.0069 (2.34)	0.0023 (2.58)	0.0071 (2.47)	0.0023 (2.24)	50.1935	
	High-Low difference	-0.0001 (-0.05)	0.0040 (3.00)	-0.0005 (-0.26)	0.0033 (2.28)	0.0189	
HIGH (TOP 33%)	Low-BLC	0.0065 (2.43)	-0.0016 (-1.53)	0.0066 (2.46)	-0.0019 (-1.30)	49.2024	4 9 . 2 0 7 3
	2	0.0077 (3.00)	-0.0008 (-0.99)	0.0052 (1.98)	-0.0020 (-1.86)	49.1958	
	3	0.008024 (3.09)	0.0001 (0.08)	0.0074 (2.80)	-0.0001 (-0.09)	49.2266	
	4	0.0072 (2.73)	0.0005 (0.69)	0.0053 (1.86)	-0.0008 (-0.67)	49.2072	
	High-BLC	0.0060 (2.08)	0.0014 (1.53)	0.0059 (1.78)	0.0031 (2.29)	49.2061	
	High-Low difference	-0.0004 (-0.26)	0.0031 (2.59)	-0.0007 (-0.31)	0.0050 (2.45)	0.0037	

5.2.3 Mispricing

As discussed at the beginning of the section, this subsection deviates from the rest of the paper with its relatively limited sample (from January 1970 to December 2016), while the rest of the paper accounts until December 2020. This portfolio adjustment was necessary, as the MISP Score database has not been updated since December 2016. Besides, high MISP scores correspond to more overpricing, while low-MISP

scores correspond to less overpricing (Stambaugh et al., 2015). For linear models like CAPM, or the seven-factor model that we employ in our study, highly overpriced assets should theoretically generate negative alphas, i.e., they should disappoint the model's expectations with lower realized returns than expected. Or, in CAPM terminology, they should be plotted under the Security Market Line (SML) (Hodnett & Hiseitt, 2012). However, as the pricing pressures of trading activities will adjust these prices downwards, expected returns will jump back to the SML equilibrium, which is theorized in CAPM and APT contexts under different limitations and assumptions (Hodnett & Hiseitt, 2012). Without delving into the differing CAPM & APT specifications related to SML, we could reasonably assume that the well-informed and rational investors could exploit the signals of mispricing by buying underpriced and (short-)selling overpriced portfolios given the fact that the market is sufficiently efficient and competitive. Alternatively, such trading activities could also result in more efficient markets. For instance, short-selling activities are shown to be a significant contributor to market efficiency, as they tend to avoid "any overvaluation" (Sobaci, Sensoy, & Erturk, 2014). In line with these adjustments, the literature typically associates overpriced (high-MISP) assets with negative returns, while underpriced assets are associated with abnormal positive returns (Cao J. et al., 2019). The results in Table 7 are clearly in line with these expectations, as a significant decrease in stock returns is observed between the three rows. Similar to the last sections, the examinations related to the results of the bivariate sorts are again focused on the examination of the significance of seven-factor alphas, primarily for the High-Low Difference of BLC quintile portfolios. The results for EW(VW) portfolios indicate the Newey-West t-statistics of

3.79 (4.29), 2.4 (3.56), and 0.82 (1.04), respectively, for portfolios that include stocks with low, mid, and high levels of the mispricing index.

Table 7: Bivariate Portfolio Analysis of Stocks on 5x3 Sorted Portfolios (Mispricing)

Double-sorted equal-weighted and value-weighted portfolios are constructed and utilized using the seven-factor model. Stocks are first sorted based on their MISP scores, and then within each MISP-sorted portfolio, they are further sorted based on the balance sheet conservativity factor (BLC) ranks. The first two columns present the breakpoints or cut-off points determined by each of these factors. The lowest (highest) 33% MISP-scored portfolios are denoted as underpriced (overpriced) in the table. Average excess returns (RET-RF) and risk-adjusted excess returns (alphas) are reported alongside the parentheses containing the respective Newey-West (1987) adjusted t-statistics (using six lags). The sample period is from January 1970 to December 2016.

MISP	BLC Quintile	EQUAL-WEIGHTED		VALUE-WEIGHTED	
		RET-RF	α_7	RET-RF	α_7
UNDERPRICED	Low Portfolio	0.0104 (5.12)	0.0009 (1.41)	0.0066 (4.01)	-0.0015 (-2.41)
	2	0.0113 (5.17)	0.0023 (4.58)	0.0063 (3.45)	-0.0005 (-0.73)
	3	0.0120 (5.31)	0.0035 (6.15)	0.0082 (3.75)	0.0023 (1.94)
	4	0.0103 (4.45)	0.0035 (5.75)	0.0079 (3.18)	0.0040 (3.14)
	High Portfolio	0.0110 (4.33)	0.0053 (6.56)	0.0086 (2.98)	0.0059 (4.13)
	High-Low difference	0.0005 (0.37)	0.4% (3.79)	0.0020 (0.91)	0.7% (4.29)
MID (MIDDLE 34%)	Low Portfolio	0.0084 (4.13)	-0.0001 (-0.19)	0.0058 (3.06)	-0.0019 (-2.04)
	2	0.0087 (3.53)	-0.0005 (-0.69)	0.0057 (2.62)	-0.0014 (-1.66)
	3	0.0088 (3.39)	0.0005 (0.81)	0.0050 (2.15)	-0.0004 (-0.48)
	4	0.0091 (3.40)	0.0028 (4.69)	0.0064 (2.24)	0.0037 (3.18)
	High Portfolio	0.0074 (2.40)	0.0030 (3.28)	0.0061 (1.83)	0.0053 (3.37)
	High-Low difference	-0.0009 (-0.46)	0.3% (2.40)	0.0003 (0.10)	0.7% (3.56)
OVERPRICED	Low Portfolio	0.0038 (1.54)	-0.0029 (-3.06)	0.0036 (1.74)	-0.0014 (-1.45)
	2	0.0028 (1.03)	-0.0044 (-5.48)	0.0017 (0.65)	-0.0042 (-4.69)
	3	0.0023 (0.81)	-0.0034 (-4.52)	0.0024 (0.83)	-0.0016 (-1.49)
	4	0.0020 (0.62)	-0.0024 (-3.65)	0.0032 (0.99)	0.0008 (0.71)
	High Portfolio	0.0013 (0.36)	-0.0017 (-1.85)	0.0017 (0.46)	0.0006 (0.41)
	High-Low difference	-0.0025 (-1.08)	0.1% (0.82)	-0.0019 (-0.71)	0.2% (1.04)

High-Low portfolio alphas still generate positive -albeit insignificant- risk-adjusted excess returns for even the most overpriced stocks for High-MISP scores, which shows the neutralizing effect of high-BLC to cover the negative returns. That would also imply that the significance of previous results is coming from either fairly priced (denoted as MID in **Table 7**) or underpriced stocks. As MISP-controlled (MID) portfolios are also generating significant risk-adjusted excess returns, it is clear that BLC is not proxied by MISP. Additionally, significant alphas for underpriced portfolios clearly indicate the dominance of high-BLC over low-MISP in terms of abnormal risk-adjusted stock return generation.

5.3 Summary Statistics

In this section, stocks are divided among quintile portfolios based on the balance sheet measures (CDA, WCA, LTDA) and their composite factor (BLC). The median of each of the return predictors for quintile portfolios sorted on each of the four discussed characteristics is provided in the subsequent tables. As discussed in Section 5.2, MISP score data are not available for the time period after December 2016. However, the portfolios are constructed using the 50-year data that extends until December 2020. The descriptive statistics for portfolios ranked by CDA, WCA, LTDA, and BLC are presented in **Table 8**, **Table 9**, **Table 10**, and **Table 11**, respectively.

Table 8: Median for Portfolios Sorted by CDA

Quintile portfolios are constructed and sorted on CDA ranks of stocks. For each of the quintile portfolios, the medians of the previously defined return predictors (or anomalies) and the difference between the highest and lowest medians are calculated. Respective t-statistics are provided in parentheses. The sample period is from January 1970 to December 2020, with the exception of the MISP, which ends in December 2016.

Quintile	β	SIZE (bn)	BM	REV	MOM	ROE	IVOL	ILLIQ (/mn)	MAX	AG	MISP
1 (lowest)	0.7340	358	0.7110	0.0039	0.0911	0.1069	0.0155	0.0762	0.0405	0.0780	51.9609
	(41.53)	(12.19)	(39.63)	(2.15)	(6.16)	(45.56)	(42.19)	(8.67)	(37.61)	(29.43)	(192.79)
2	0.8138	393	0.6623	0.0044	0.0993	0.1088	0.0164	0.1260	0.0434	0.0804	50.4334
	(37.75)	(8.52)	(36.43)	(2.19)	(6.02)	(57.83)	(42.09)	(7.72)	(37.33)	(25.56)	(243.77)
3	0.8859	519	0.6039	0.0049	0.1078	0.1131	0.0174	0.1930	0.0456	0.0829	49.1447
	(40.01)	(7.73)	(27.25)	(2.27)	(5.98)	(68.88)	(49.03)	(7.21)	(43.11)	(23.81)	(405.30)
4	0.9931	485	0.5421	0.0059	0.1183	0.1116	0.0191	0.2600	0.0499	0.0885	47.6095
	(85.26)	(8.21)	(23.35)	(2.62)	(6.36)	(51.13)	(41.48)	(6.65)	(39.03)	(25.52)	(259.41)
5 (highest)	1.0808	297	0.4774	0.0058	0.1326	0.0961	0.0215	0.3010	0.0552	0.1196	47.8980
	(53.05)	(9.94)	(16.30)	(2.49)	(6.41)	(20.51)	(29.48)	(6.14)	(28.19)	(26.49)	(140.17)
High-Low Difference	0.3468	-60.8	-0.2336	0.0019	0.0415	-0.0107	0.0060	0.2250	0.0147	0.0416	-4.0628
	(10.52)	(-6.41)	(-13.39)	(1.39)	(2.89)	(-3.12)	(11.51)	(5.30)	(10.25)	(10.36)	(-7.67)

Table 9: Median for Portfolios Sorted by WCA

Quintile portfolios are constructed and sorted on WCA ranks of stocks. For each of the quintile portfolios, the medians of the previously defined return predictors (or anomalies) and the difference between the highest and lowest medians are calculated. Respective t-statistics are provided in parentheses. The sample period is from January 1970 to December 2020, with the exception of the MISP, which ends in December 2016.

Quintile	β	SIZE (bn)	BM	REV	MOM	ROE	IVOL	ILLIQ (/mn)	MAX	AG	MISP
1 (lowest)	0.6861	917	0.5836	0.0053	0.1081	0.1146	0.0150	0.0621	0.0392	0.0723	53.0595
	(42.73)	(9.15)	(26.41)	(3.16)	(7.97)	(62.31)	(47.23)	(5.95)	(40.19)	(24.30)	(175.12)
2	0.8956	753	0.5522	0.0054	0.1073	0.1130	0.0174	0.0997	0.0455	0.0797	49.3419
	(58.12)	(8.28)	(24.67)	(2.57)	(6.40)	(53.90)	(44.39)	(6.58)	(41.26)	(21.98)	(363.86)
3	0.9663	526	0.5616	0.0056	0.1086	0.1141	0.0184	0.1530	0.0478	0.0853	47.4155
	(67.07)	(8.14)	(23.35)	(2.55)	(6.17)	(58.57)	(42.70)	(7.18)	(40.20)	(23.22)	(439.27)
4	1.0220	355	0.5539	0.0054	0.1070	0.1112	0.0199	0.2310	0.0516	0.0942	46.5605
	(105.38)	(8.39)	(23.29)	(2.34)	(5.79)	(52.15)	(37.13)	(7.22)	(35.79)	(25.97)	(304.30)
5 (highest)	1.1635	222	0.4818	0.0044	0.1082	0.0789	0.0231	0.3440	0.0591	0.1112	46.4164
	(68.60)	(9.58)	(18.71)	(1.81)	(5.06)	(12.11)	(33.63)	(6.98)	(32.14)	(22.19)	(148.39)
High-Low Difference	0.4774	-695	-0.1018	-0.0009	0.0001	-0.0357	0.0081	0.2820	0.0199	0.0389	-6.6431
	(16.80)	(-8.96)	(-10.13)	(-0.59)	(0.01)	(-6.74)	(17.28)	(7.11)	(15.52)	(8.07)	(-12.19)

Table 10: Median for Portfolios Sorted by LTDA

Quintile portfolios are constructed and sorted on LTDA ranks of stocks. For each of the quintile portfolios, the medians of the previously defined return predictors (or anomalies) and the difference between the highest and lowest medians are calculated. Respective t-statistics are provided in parentheses. The sample period is from January 1970 to December 2020, with the exception of the MISP, which ends in December 2016.

Quintile	B	SIZE (bn)	BM	REV	MOM	ROE	IVOL	ILLIQ (/mn)	MAX	AG	MISP
1 (lowest)	0.9364	219	0.5079	0.0045	0.1093	0.1062	0.0199	0.2420	0.0507	0.1002	45.3540
	(90.23)	(12.01)	(24.78)	(2.29)	(6.57)	(33.03)	(33.26)	(7.85)	(32.49)	(30.52)	(229.37)
2	0.8538	259	0.6219	0.0048	0.1123	0.1109	0.0179	0.1900	0.0470	0.0961	47.8875
	(52.99)	(11.36)	(35.02)	(2.27)	(6.30)	(43.17)	(35.87)	(6.41)	(34.90)	(32.15)	(206.53)
3	0.8560	445	0.6338	0.0052	0.1098	0.1115	0.0170	0.1480	0.0448	0.0849	47.9734
	(40.03)	(7.59)	(28.84)	(2.56)	(6.39)	(57.66)	(43.00)	(7.19)	(39.01)	(26.99)	(317.51)
4	0.8772	771	0.6410	0.0048	0.1026	0.1111	0.0166	0.1390	0.0438	0.0765	50.2373
	(43.82)	(7.52)	(24.29)	(2.34)	(6.16)	(71.44)	(45.86)	(6.46)	(41.27)	(24.78)	(325.38)
5 (highest)	0.9175	616	0.5871	0.0049	0.1015	0.1075	0.0177	0.1080	0.0459	0.0799	56.1618
	(45.21)	(8.43)	(24.17)	(2.42)	(6.19)	(51.98)	(46.05)	(7.97)	(39.89)	(20.26)	(266.92)
High-Low Difference	-0.0189	397	0.0792	0.0004	-0.0078	0.0014	-0.0021	-0.1340	-0.0048	-0.0203	10.8078
	(-0.85)	(7.15)	(8.92)	(0.49)	(-1.11)	(0.73)	(-6.01)	(-7.31)	(-5.30)	(-7.67)	(42.07)

Table 11 Median for Portfolios Sorted by BLC

Quintile portfolios are constructed and sorted on BLC ranks of stocks. For each of the quintile portfolios, the medians of the previously defined return predictors (or anomalies) and the difference between the highest and lowest medians are calculated. Respective t-statistics are provided in parentheses. The sample period is from January 1970 to December 2020, with the exception of the MISP, which ends in December 2016.

Quintile	B	SIZE (bn)	BM	REV	MOM	ROE	IVOL	ILLIQ (/mn)	MAX	AG	MISP
1 (lowest)	0.7608	889	0.6226	0.0048	0.0965	0.1105	0.0155	0.0563	0.0405	0.0700	54.1089
	(41.30)	(8.64)	(26.36)	(2.61)	(6.54)	(59.39)	(45.63)	(6.62)	(38.41)	(22.70)	(249.89)
2	0.9239	602	0.5884	0.0049	0.0998	0.1103	0.0178	0.1320	0.0464	0.0786	49.9797
	(55.05)	(8.12)	(25.11)	(2.26)	(5.83)	(58.89)	(45.36)	(8.13)	(42.63)	(21.65)	(419.38)
3	0.9612	541	0.5609	0.0053	0.1121	0.1121	0.0185	0.1980	0.0482	0.0853	47.3836
	(71.41)	(7.99)	(22.96)	(2.41)	(6.24)	(60.04)	(41.84)	(6.57)	(40.19)	(24.27)	(327.87)
4	1.0330	354	0.5043	0.0057	0.1157	0.1083	0.0203	0.2470	0.0524	0.0984	45.2850
	(128.37)	(8.46)	(22.50)	(2.55)	(6.23)	(40.94)	(35.99)	(6.60)	(34.40)	(27.79)	(348.27)
5 (highest)	1.1500	222	0.4320	0.0053	0.1245	0.0906	0.0231	0.4370	0.0591	0.1157	43.6895
	(62.36)	(9.93)	(19.62)	(2.16)	(5.74)	(15.66)	(32.26)	(6.40)	(30.79)	(23.92)	(129.42)
High-Low Difference	0.3893	-667	-0.1906	0.0005	0.0280	-0.0199	0.0075	0.3810	0.0186	0.0457	-10.4194
	(11.84)	(-8.15)	(-22.31)	(0.32)	(1.82)	(-4.08)	(14.71)	(6.23)	(12.98)	(10.05)	(-21.60)

There are no immense disparities between the descriptive characteristics and patterns related to the CDA (**Table 8**), WCA (**Table 9**), and LTDA (**Table 10**). Needless to say, LTDA is expected to contain inverse patterns to the first two measures, as observed in the tables. However, there are a few idiosyncrasies of those measures that can be addressed according to the table results. For instance, unlike other measures, the CDA seems to have a statistically significant correlation with the MOM, which effectively means that the companies holding more cash relative to their total assets tend to have more cumulative returns over the past 11 months. Another idiosyncrasy is LTDA-ranked portfolios' statistical indifference to ROE. In other words, equity profitability does not differ significantly for the lowest and highest portfolios ranked by the LTDA ratio. On the other hand, **Table 11** presents an extensive overview of the trends and variations for the ranked portfolios based on the composite factor (BLC).

According to the summary statistics reported in **Table 11**, some interesting trends of the ranked portfolios can shed light on the understanding of financial risk and mispricing related to balance sheet conservativity. Firstly, it must be noted that the idiosyncrasies related to CDA and LTDA do not exist in the composite factor, and the remaining patterns are quite coherent. Interestingly, we see a monotonic increase in β measure between the highest-BLC and lowest-BLC portfolios, which would also mean that those companies that are in a high likelihood of systematic risk exposure may choose to follow a more "conservative" strategy by holding more cash, less long-term debt, and more working capital. However, we also observe a monotonic decrease in size as the BLC-rank of the portfolio increases (and again, the difference between the extremes is statistically significant). The decrease in size for higher BLC

portfolios could also be a sign of underreaction, as the information costs for the stocks of smaller companies can be vastly higher than those of big corporations. Investor inattention to smaller companies could also provide an alternative explanation. Another interesting pattern was the monotonic and significant increasing trend of IVOL in parallel to the BLC rank of the portfolios, which effectively means that high-BLC portfolios tend to include more severely volatile stocks. This pattern would again be a sign of mispricing due to underreaction, as it can be extremely costly to exploit arbitrage opportunities for the investors (i.e., costly arbitrage), and thus, the investors may underreact to high-IVOL stocks. Besides, a similar monotonic and significant pattern is also observable for the illiquidity measure (ILLIQ). It is, again, might point to an underreaction story: Investors would hesitate to buy the stock of an illiquid company, and even if they wanted to do so, it is highly likely they would not be able to find anyone to sell the stock. However, these behavioral attributions are mere assumptions, and it is difficult to reach a conclusion based on only descriptive statistics.

5.4 Fama-MacBeth Regressions

The Fama-MacBeth two-step procedure is applied individually for each of the three balance sheet measures used in this study. The findings of the multivariate regressions (**Table 12**) show that, when tested against the known return predictors and anomalies in the literature, the LTDA measure has a statistically significant but negative risk premium in contrast to the CDA and WCA measures, which have positive-but-weak risk premiums. These analyses show that LTDA is the only

balance sheet measure with the capability to generate a significant and isolated risk premium. However, it is important to note that the models incorporating these three variables may be inadequate in fully capturing the complexities of asset pricing, as evidenced by the predominantly significant intercept terms.

Table 12: Fama-MacBeth (Multivariate) Regression Results

The table below exhibits the average slopes, commonly known as risk premiums, are derived from month-by-month cross-sectional regressions of portfolio returns using the Fama-MacBeth (1973) strategy which was utilized to test the significance of BLC parameters' risk premiums (i.e., λ_{CDA} , λ_{WCA} , λ_{LTDA}) against the well-known return predictors in the literature. Hence, we employ an enhanced model of risk predictor with ten extra elements included alongside each balance sheet ratio. The presented t-statistics are Newey-West heteroskedasticity and autocorrelation (HAC) adjusted using six months lag and reported in parentheses. Factor coefficients and t-statistics that correspond to the respective balance sheet measures (i.e., λ_{CDA} , λ_{WCA} , λ_{LTDA}) are bolded. The sample period is from January 1970 to December 2020.

	CDA	WCA	LTDA
Intercept	0.0282 (3.77)	0.0277 (3.47)	0.0303 (3.94)
Factor λ	0.0054 (1.87)	0.0022 (1.34)	-0.0038 (-2.11)
β	0.0010 (0.72)	0.0004 (0.32)	0.0005 (0.35)
SIZE	-0.0007 (-2.58)	-0.0006 (-2.35)	-0.0007 (-2.58)
BM	0.0016 (2.54)	0.0014 (2.21)	0.0014 (2.07)
REV	-0.0396 (-10.15)	-0.0383 (-9.52)	-0.0383 (-9.54)
MOM	0.0070 (5.52)	0.0067 (5.16)	0.0068 (5.15)
ILLIQ	32.2396 (0.32)	99.3305 (0.79)	85.5393 (0.68)
IVOL	-0.3555 (-8.69)	-0.3467 (-8.47)	-0.3461 (-8.46)
MAX	0.0372 (4.56)	0.0390 (4.83)	0.0393 (4.89)
AG	-0.0041 (-6.34)	-0.0045 (-6.85)	-0.0044 (-6.60)
ROE	0.0023 (2.44)	0.0024 (2.43)	0.0023 (2.42)

5.5 Societal Impact

The outcomes of our research suggest important implications not just for investors, but also for society. We believe that incorporating balance sheet measures into the existing risk-factor models will enhance the understanding of balance sheet evaluations regarding risk attachment. As balance sheet evaluations are a decisive part of lending decisions, we believe that the financial sector (especially the commercial lenders) could highly benefit from the perspective of this study. Because better-evaluated balance sheets will result in better lending decisions and thus more stability for the financial sector, our study's contributions on the financial stability will enhance the public trust in the markets.

CHAPTER 6

CONCLUSION

Our research aimed to investigate the relationship between balance sheet indicators and stock returns, focusing specifically on the composite balance sheet factor, namely the balance sheet conservativity factor (BLC). Rigorous analytical techniques are employed to explore this relationship, including univariate and bivariate portfolio analyses and Fama-Macbeth regressions. The dataset utilized in this study comprises monthly adjusted closing prices of stocks traded on prominent stock exchanges, including the AMEX, NASDAQ, and NYSE, spanning a substantial period from January 1970 to December 2020. The measures (CDA, WCA, LTDA) and their composite factor (BLC) are incorporated in the univariate and bivariate portfolio analyses based on the seven-factor model under the Fama-French framework.

The results of univariate portfolio analyses indicate that the composite factor (BLC) and its parameters (i.e., CDA, WCA, and LTDA) exhibit statistical significance in risk-adjusted return differences (α_7) between the extreme portfolios (both EW and VW). The statistical significance of seven-factor alphas may also point to an investment strategy for buying the highest-scored and shorting the lowest-scored portfolios regarding CDA, WCA, and the precise opposite for LTDA. Similarly, the univariate sorts show that their linearly constructed composite factor, BLC, also generates significant risk-adjusted excess return differences between the extreme portfolios. The bivariate portfolio sorts of BLC (when controlled for size and illiquidity) confirmed this result, indicating that regardless of the size and illiquidity

percentile, a higher BLC rank is significantly associated with risk-adjusted excess return. On the other hand, statistically significant high-low portfolio alphas for MISP-controlled portfolio sorts indicated that the abnormal returns associated with BLC are either not caused by mispricing, or, cannot be proxied by the existing MISP score anomalies. This conclusion is interesting in the sense that, previous discussions concerning the efficiency of the risk factor models are becoming increasingly valid for mispricing measures.

Summary statistics showed that the high-BLC portfolios are characteristically smaller, more illiquid, and more severely volatile portfolios. Such characteristics are commonly associated with underreaction, in accordance with behavioralist explanations of mispricing (e.g., costly arbitrage, information cost, investor inattention). High-BLC portfolios are also relatively underpriced compared to their low-BLC counterparts, which may indeed support a demand-side underreaction effect. However, high-BLC portfolios also tend to have higher market betas, which would challenge the mispricing story by backing the contrary assumption to explain the results: conservative corporate policies may reflect themselves in balance sheets to avoid the consequences of their high-risk exposure to the market movements. Additionally, the success of BLC in MISP-controlled portfolio sorts (in terms of generating significant long-short portfolio alphas) also challenges the mispricing explanations. These results seem to indicate a mixed effect of both risk and underreaction-based mispricing.

The comprehensive findings from the Fama-MacBeth regressions also tested the effectiveness of the separate parameters of the balance sheet conservativity factor

(CDA, WCA, and LTDA) for generating isolated risk-premiums, when accounted against ten different return predictors. The results for CDA and WCA indicated a positive-but-weak association between these measures and anticipated stock returns. On the other hand, LTDA proved to be a strong -and negative- indicator of stock returns that is capable of generating negatively significant risk premiums. Therefore, LTDA was the only balance sheet measure associated with significant λ 's, and, the effects of CDA and WCA on stock returns may be proxied by other return predictors/anomalies. Consequently, risk-based effects in BLC's abnormal return generation may be driven by the LTDA parameter. The other measures may be more prone to mispricing. Regardless of the conclusions about BLC, LTDA itself was proven to be a significant indicator of abnormal returns, and may itself be a risk factor, with its proven empirical robustness due to significant λ and α scores.

The collective findings in this study suggest that BLC is a significant predictor of stock returns. Of the three balance sheet metrics that BLC is composed of, LTDA is the only parameter with the capability of isolating significant risk premiums. Hence, we can conclude that LTDA is significantly priced in the cross-section of stock returns. The results also indicated a mixed effect of both risk and underreaction-driven mispricing that could be explained by several behavioral attributes (information costs, costly arbitrage, investor inattention, etc.).

The findings of this study contribute significantly to the understanding of asset pricing dynamics and the relationship between balance sheet indicators and stock returns. In addition to providing insights into the complex mechanisms behind the financial risk and mispricing, this study implicitly favors long-short (high-low)

portfolio investments based on BLC ranks and its parameters (especially -LTDA). Another implicit suggestion is for the issuers of these stocks to follow conservative financial policies (following the context of this paper's terminology) to tackle negative expected returns associated with their stocks' overvaluation. As BLC has been proven to neutralize (or even reverse) the negative effects of overvaluation, firms can protect themselves (and their shareholders) from short-seller exploitation. Likewise, these results would subtly recommend short-selling exploiters of overpricing to target the stocks of firms with lower BLC scores.

References

- Aharoni, G., Grundy, B., & Zeng, Q. (2013). Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama French analysis. *Journal of Financial Economics*, 110(2), 347-357. doi: 10.1016/j.jfineco.2013.08.003
- Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1), 31-56. doi: 10.1016/S1386-4181(01)00024-6
- Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), 259-299. doi: 10.1111/j.1540-6261.2006.00836.x
- Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2), 427-446. doi: 10.1016/j.jfineco.2010.08.014
- Bali, T. G., Brown, S., & Tang, Y. (2017). Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics*, 126(3), 471-489. doi: 10.1016/j.jfineco.2017.09.005
- Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49(3), 307-343. doi: 10.1016/S0304-405X(98)00027-0
- Brennan, M. J. (1970). Taxes, market valuation and corporate financial policy. *National Tax Journal*, 23(4), 417-427. doi: 10.1086/ntj41792223
- Campbell, J. Y. (1996). Understanding risk and return. *Journal of Political Economy*, 104(2), 298-345. doi: 10.1086/262026

- Cao, J., Titman, S., Zhan, X., & Zhang, W. (2019). ESG preference and market efficiency: Evidence from mispricing and institutional trading. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3353623
- Cao, J., Titman, S., Zhan, X., & Zhang, W. (2022). ESG preference, institutional trading, and stock return patterns. *Journal of Financial and Quantitative Analysis*, 1-35. doi: 10.1017/S0022109022000916
- Cao, Z., Chelikani, S., Kilic, O., & Wang, X. (2022). Implied volatility spread and stock mispricing. *Journal of Behavioral Finance*, 1-13. doi: 10.1080/15427560.2022.2085278
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57-82. doi: 10.1111/j.1540-6261.1997.tb03808.x
- Chen, A. Y., & Zimmermann, T. (2022). Open source cross-sectional asset pricing. *Critical Finance Review*, 27(2), 207-264. doi: 10.2139/ssrn.3604626
- 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. doi: 10.1111/j.1540-6261.2008.01370.x
- Czapkiewicz, A., Wójtowicz, T., & Zaremba, A. (2023). Idiosyncratic risk and cross-section of stock returns in emerging European markets. *Economic Modelling*, 124, 106322. doi: 10.1016/j.econmod.2023.106322
- Dai, Z., Maydew, E., Shackelford, D. A., & Zhang, H. H. (2008). Capital gains taxes and asset prices: Capitalization or lock-in? *The Journal of Finance*, 63(2), 709-742. doi: 10.1111/j.1540-6261.2008.01329.x
- Dybvig, P. H., & Ross, S. A. (1985). Yes, the APT is testable. *The Journal of Finance*, 40(4), 1173-1188. doi: 10.1111/j.1540-6261.1985.tb02370.x

- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), 383-417. doi: 10.2307/2325486
- Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, 46(5), 1575-1617. doi: 10.1111/j.1540-6261.1991.tb04636.x
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427-465. doi: 10.1111/j.1540-6261.1992.tb04398.x
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56. doi: 10.1016/0304-405x(93)90023-5
- Fama, E. F., & French, K. R. (1998). Taxes, financing decisions, and firm value. *The Journal of Finance*, 53(3), 819-843. doi: 10.1111/0022-1082.00036
- Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, 63(4), 1653-1678. doi: 10.1111/j.1540-6261.2008.01371.x
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22. doi: 10.1016/j.jfineco.2014.10.010
- Fama, E. F., & French, K. R. (2018). Choosing factors. *Journal of Financial Economics*, 128(2), 234-252. doi: 10.1016/j.jfineco.2018.02.012
- Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607-636. doi: 10.1086/260061
- Gromb, D., & Vayanos, D. (2010). Limits of arbitrage. *Annual Review of Financial Economics*, 2(1), 251-275. doi: 10.1146/annurev-financial-073009-104107
- Hanlon, M., & Heitzman, S. (2010). A review of tax research. *Journal of Accounting and Economics*, 50(2-3), 127-178. doi: 10.1016/j.jacceco.2010.09.002

- Hodnett, K., & Hsieh, H. H. (2012). Capital market theories: Market efficiency versus investor prospects. *International Business & Economics Research Journal (IBER)*, 11(8), 849-862. doi: 10.19030/iber.v11i8.7163
- Haugen, R. A., & Baker, N. L. (1996). Commonality in the determinants of expected stock returns. *Journal of Financial Economics*, 41(3), 401-439. doi: 10.1016/0304-405X(95)00868-F
- Hou, K., Xue, C., & Zhang, L. (2014). Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3), 650-705. doi: 10.1093/rfs/hhu068
- Hou, K., Xue, C., & Zhang, L. (2022). *Technical Document: Factors*. Retrieved from https://global-q.org/uploads/1/2/2/6/122679606/factorstd_2020july.pdf
- Ince, B., & Ozsoylev, H. N. (2020). Demand for idiosyncratic lottery-like payoffs and the cross-section of expected returns. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3729163
- Ince, B. (2022). Forecasted unemployment and the cross-section of stock returns. *SSRN Electronic Journal*. doi: 10.2139/ssrn.4048669s
- Ince, B. (2022a). Liquidity components: Commonality in liquidity, underreaction, and equity returns. *Journal of Financial Markets*, 60(C). doi: 10.1016/j.finmar.2022.100730
- 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. doi: 10.1111/j.1540-6261.1993.tb04702.x
- Jensen, M. C., Black, F., & Scholes, M. S. (1972). The capital asset pricing model: Some empirical tests. *Studies in the Theory of Capital Markets*. Retrieved from <https://ssrn.com/abstract=908569>

- Kruschwitz, L., & Löffler, A. (2009). Do taxes matter in the CAPM? *Business Research*, 2(2), 171-178. doi: 10.1007/BF03342709
- Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47(1), 13-37. doi: 10.2307/1924119
- Litzenberger, R. H., & Ramaswamy, K. (1982). The effects of dividends on common stock prices tax effects or information effects? *The Journal of Finance*, 37(2), 429-443. doi: 10.2307/2327346
- Loh, R. K. (2010). Investor inattention and the underreaction to stock recommendations. *Financial Management*, 39(3), 1223-1252. doi: 10.1111/j.1755-053X.2010.01110.x
- Maiti, M. (2021). *Applied Financial Econometrics Theory, Method and Applications*. Palgrave Macmillan. doi: 10.1007/978-981-16-4063-6
- Mayers, D. (1973). Nonmarketable assets and the determination of capital asset prices in the absence of a riskless asset. *The Journal of Business*, 46(2), 258-267. doi: 10.1086/295528
- Merton, R. C. (1972). An analytic derivation of the efficient portfolio frontier. *Journal of Financial and Quantitative Analysis*, 7(4), 1851-1872. doi: 10.2307/2329621
- Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, 867-887. doi: 10.2307/1913811
- Newey, W., & West, K. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 28(3), 777-787. doi: 10.2307/2526578

- Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1), 1-28. doi: 10.1016/j.jfineco.2013.01.003
- Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3), 642-685.
- Pastor, L. & Stambaugh, R. F. (2019). Liquidity risk after 20 years. *Critical Finance Review*, 8(1-2), 277-299. doi: 10.2139/ssrn.3371948
- Penman, S. H., Reggiani, F., Richardson, S. A., & Tuna, İ. (2018). A framework for identifying accounting characteristics for asset pricing models, with an evaluation of book-to-price. *European Financial Management*, 24(4), 488-520. doi: 10.1111/eufm.12171
- Penman, S. H., & Zhang, X. J. (2021). Accounting for asset pricing factors. *Columbia Business School Research Paper*. doi: 10.2139/ssrn.3881177
- Penman, S., & Zhu, J. (2022). An accounting-based asset pricing model and a fundamental factor. *Journal of Accounting and Economics*, 73(2–3), 101476. doi: 10.1016/j.jacceco.2021.101476
- Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics*, 42(1–2), 35-52. doi: 10.1016/j.jacceco.2006.04.002
- Ross, S. A. (1976). The arbitrage theory of capital asset pricing, *Journal of Economic Theory*, 13, 341-360. doi: 10.1016/0022-0531(76)90046-6
- Shanken, J. (1982). The arbitrage pricing theory: is it testable? *The Journal of Finance*, 37(5), 1129-1140. doi: 10.1111/j.1540-6261.1982.tb03607.x
- Shanken, J. (1985). Multi-beta CAPM or equilibrium-APT?: A reply. *The Journal of Finance*, 40(4), 1189-1196. doi: 10.2307/2328402

- Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance*, 939-974. doi: 10.1016/s1574-0102(03)01024-0
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425-442. doi: 10.1111/j.1540-6261.1964.tb02865.x
- Sobaci, C., Sensoy, A., & Erturk, M. (2014). Impact of short selling activity on market dynamics: Evidence from an emerging market. *Journal of Financial Stability*, 15(C), 53-62. doi: 10.1016/j.jfs.2014.08.010
- Stambaugh, R. F., Yu, J., & Yuan, Y. (2015). Arbitrage asymmetry and the idiosyncratic volatility puzzle. *The Journal of Finance*, 70(5), 1903-1948. doi: 10.1111/jofi.12286
- Stambaugh, R. F (n.d.). *Stambaugh and Yuan "Mispricing Factors" data*. Retrieved from <https://finance.wharton.upenn.edu/~stambaug/>
- Watanabe, A., Xu, Y., Yao, T., & Yu, T. (2013). The asset growth effect: Insights from international equity markets. *Journal of Financial Economics*, 108(2), 529-563. doi: 10.1016/j.jfineco.2012.12.002