Firm fundamentals, stochastic risk premiums, and the cross-section of expected returns

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Abstract

This thesis aims to understand the role of firm fundamentals in measuring the firm-level risk and expected returns in the cross-section. It contains three chapters and proceeds as follows. Chapter 1 presents the core research questions, outlines the key motivations, and summarizes the main results.

Chapter 2 develops a novel theoretically derived approach towards estimating firm level expected stock returns. I show that the firm-level one-period-ahead expected stock return is a linear combination of book-to-market ratio, forward earnings yield, and a variable summarizing one-period-ahead value-relevant 'other information'. This 'other information' can be inferred from the firm's one-period-ahead earnings expectation and the current stock price. The empirical evidence shows that the expected return estimates exhibit meaningful associations with a wide range of firm characteristics and are significantly positively associated with future realized returns.

Chapter 3 tests the cross-sectional associations of a set of firm fundamentals and stock returns against 'beta'-based and 'alpha'-based explanations jointly in a novel two-step testing framework. The new testing methodology builds on the intuition that, if a variable predicts stock returns due to its ability to proxy for firm betas, then its return predictive coefficients must vary consistently with rational expectations of the future realizations of corresponding risk factors. My test results suggest that the return predictive ability of many firm fundamentals is mostly consistent with 'alpha'-based explanations.

Chapter 4 summarizes the key contributions and results of the thesis.

Dedication

To my loving wife, Daisy, for supporting me through the hardest moments.

To my parents, for teaching me the value of perseverance.

Statement of originality

I declare that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I declare that the intellectual content of this thesis is the product of my own work and that all the assistance and guidance received in preparing this thesis and sources have been acknowledged.

Chapter 2 of this thesis has been extended and adapted to a working paper titled 'Firm fundamentals, one-period-ahead earnings expectations and expected returns' co-authored with Pengguo Wang and Demetris Christodoulou. My contributions to the paper include generalizing the theoretical development, designing and implementing validation tests, and writing the first draft of the paper. Chapter 2 mainly reflects my own contribution.

Chapter 3 of this thesis has been adapted to a solo-authored working paper titled 'Alpha versus Beta: Firm fundamentals in the cross-section of expected returns'.

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Chapter 1

Introduction and motivation

There is a growing consensus that firm fundamentals, as measured by accounting data, convey important information about the cross-section of stock returns. This notion gives rise to two crucial research questions that are at the heart of empirical fundamental analysis:

RQ1 How can one use firm fundamentals to construct valid measures of *ex ante* expected returns?

RQ2 Is the return predictive information in firm fundamentals attributed to risk or mispricing?

Chapter 2 is an attempt to address RQ1. While there is no shortage of expected returns measures that utilize firm fundamentals, few existing measures exhibit meaningful associations with future realized returns in the cross-section. The new measure is based on a linear pricing rule generalized to a setting that allows for time variation in expected returns. I show that the firm-level one-period-ahead expected return is a linear combination of forward earnings yield, book-to-market ratio, and a variable summarizing one-period-ahead 'other information'. This 'other information' is implied by the firm's one-period-ahead earnings expectation and the current stock price. The new measure is significantly positively associated with future realized returns out-of-sample, and this positive association is robust to controlling for contemporaneous cash flows and expected return news and a wide range of firm characteristics. Hence, the new measure provides a meaningful summary of the cross-section of expected returns.

Chapter 3 examines RQ2. In asset pricing theory, firm fundamentals explain the cross-section of stock returns if and only if they are signals for the cross-section of firm-level exposures to common risk factors (i.e. 'betas'). Alternatively, firm fundamentals can forecast stock returns if they are predictably mispriced in the cross-section, giving rise to 'alphas'. I design an innovative two-step testing methodology to explicitly dissect these two potential explanations in the cross-sectional relation between firm fundamentals and stock returns. The results suggest that, while some firm fundamental variables are modestly associated with firms' betas, the return predictive ability of many firm fundamentals at the firm level is mostly attributed to their contributions to alphas. This casts doubt on the validity of the practice to measure firm-level risk using the realized associations between firm fundamentals and stock returns.

Chapter 2

Firm fundamentals, stochastic risk premiums, and implied expected returns

2.1 Introduction

Estimating expected returns remains a challenge central to research and practice in accounting and finance. In this chapter, I develop a novel approach to identifying firm-level one-period-ahead expected returns. Motivated by Ashton and Wang (2013), the approach is based on a linear pricing rule similar to that of Ohlson (1995) and Feltham and Ohlson (1995) but re-developed in a setting that allows for time variation in expected returns. I show that the firm-level one-period-ahead expected return is a linear combination of forward earnings yield, book-to-market ratio, and a variable summarizing implied next-period other information.

The construction of my firm-level expected return measure can be described in three steps. First, I estimate a set of common valuation parameters for a portfolio of homogeneous firms, including portfolio average costs of capital and growth rates in the other information term. Consistent with long-standing industry practice, I use industry partitions to group homogeneous firms in this step. Second, I use these portfolio-level parameter estimates as approximate firm-specific valuation parameters to explicitly estimate the implied other information term in the no-arbitrage market price. Finally, I combine the portfolio-level parameters with firm-specific forward earnings yield, book-to-market ratio and implied other information to proxy for expected one-period-ahead returns. .

I validate my new measure of one-period-ahead expected returns in a US sample of up to 85,385 firm-year observations from 1985 to 2014. I first show that the new measure generates an *ex ante* monotonic decile ranking of one-period-ahead expected returns. An investor who follows a long-short portfolio based on the measure earns on average 9% hedge returns per annum. The expected return estimates also show consistent relations with a set of firm-level return predictive variables, including firm size, financial leverage, CAPM beta, net operating assets growth, accruals, sales growth and investment.

In multivariate regression tests, I find that, unlike many implied cost of capital (ICC) estimates, the predictive coefficient on the expected return measure remains significantly positive after controlling for contemporaneous cash flow news, expected return news, and other return predictive variables. Results of the Easton and Monahan (2005) regression test show that the regression coefficient on expected return estimates is highly significant and statistically indistinguishable from one, consistent with theoretical expectation regarding the validity of expected return measures.

This chapter proceeds as follows. Section 2.2 discusses how the new model of expected returns relates to existing models. Section 2.3 details the theoretical foundations of this study and derives the new measure of expected return. Section 2.4 outlines the data collection and management procedures and obtains empirical estimates of the expected returns. Section 2.5 presents portfolio-based validation tests of the association of the expected return measure with realized returns and firm characteristics. Section 2.6 tests the association of the new measure of expected return with future realized returns through pooled and cross-sectional regressions. Section 2.7 summarizes the chapter.

2.2 Existing models for measuring expected returns

In this section, I provide a detailed review of existing methods for measuring expected returns and compare them with the new approach developed in this study.

2.2.1 Factor models

Factor models are deeply rooted in asset pricing theories and are regarded as the 'orthodox' approach to measuring expected returns, but the main use of factor models is to *explain* realized returns through a small number of common risk factors, rather than to construct *ex ante* measures of expected returns. Given a factor model, the construction of an expected return measure can be described in three steps. First, use time-series regressions of firms' past stock returns on past realizations of risk factors to obtain the firms' factor betas (i.e. the firm's exposure to the risk factors). Second, estimate the risk premiums associated with the risk factors using either sample mean factor realizations or cross-sectional regressions.[1] Finally, combine the estimated betas and risk

[1] If the risk factors are returns or excess returns, then the risk premiums are their expected values, which may be estimated by taking the sample means. Alternatively, cross-sectional regressions of sample average returns on the factor betas estimated from the first step can be used, so that the slope coefficients are regarded as the risk premium estimates. The latter approach does not restrict the risk premiums to equate the sample means of factor realizations.

premiums to obtain expected return estimates.[2] However, it has been shown that leading factor models yield no meaningful predictive power for future realized returns (Lyle and Wang 2015).

One common explanation for the failure is due to the inevitable use of noisy *ex post* realized returns. Average realized returns are poor measures of forward-looking risk premiums and factor betas estimated from past returns are often poorly measured (Fama and French 1997; Elton 1999). Average realized returns can substantially deviate from expected returns. For instance, a stock with a recent history of low returns may have incurred an upward revision in its expected return (i.e. positive discount rate news). Thus low average realized returns may be paired with high expected returns (Pástor et al. 2008). In addition, Penman and Zhu (2017) also find that beta estimates from lagged samples are considerably different from those estimated from forward samples, suggesting that past betas are not reliable proxies for future betas. The expected return is inherently an *ex ante* concept. It is formed within investors' forward expectations conditional on the real-time information they observe. As the conditioning information set changes, expected returns and their determinants also change. While asset pricing theory admits time-varying conditioning information, empirical implementations of factor models typically assume that the factor risk premiums and firm risk exposure (the 'betas') formed with respect to the past information set carry forward to the future.

Using factor models to construct expected return measures is also plagued by difficulties in identifying and justifying the factor structure underlying stock returns. The Capital asset pricing model (CAPM) is a tight and robust implication of many theoretical models, but it notoriously fails to describe cross-sectional returns and expected returns Fama and French (1992, 1996). Merton's (1973) intertemporal CAPM (ICAPM) and Ross's (1976) arbitrage

[2] See Lyle and Wang (2015), Lee et al. (2015) and Dittmar and Lundblad (2017) for applications of this procedure.

pricing theory (APT) provide theoretical motivation for multifactor models but do not supply guidance for selecting factors. Thus, most multifactor models are empirically motivated by evidence that some variables appear to predict returns, without clear economic interpretations (e.g. Fama and French 1992; Carhart 1997; Chen et al. 2011; Hou et al. 2015).[3] Now that there are more than 300 variables found to predict stock returns, it is not clear which of these variables correspond to robust systematic risk factors (Cochrane 2009; Green et al. 2013, 2016; Clarke 2016).

2.2.2 Implied cost of capital models

Proposed as a potential solution, ICC models use expected accounting-based payoff measures (e.g. earnings) and stock prices to estimate expected returns from valuation models, such as the residual income valuation (RIV) model and Ohlson and Juettner-Nauroth's (2005) abnormal earnings growth (AEG) model (Claus and Thomas 2001; Gebhardt et al. 2001; Easton et al. 2002; Gode and Mohanram 2003; Easton 2004; Pástor et al. 2008; Nekrasov and Ogneva 2011). ICC models bypass the difficulty in specifying the factor structure of returns and estimating the factor betas and premiums by exploiting the present value relation and solve for expected returns as a primitive valuation input.

Despite their use of forward-looking data, these models rely on arbitrary assumptions about terminal growth rates and dividend policies, and all implicitly assume a constant rate of expected return.[4] Easton and Monahan (2005) and Lee et al. (2015) find that leading ICC estimates contain substantial measurement errors and thus are poorly associated with cross-sectional realized returns.

[3] Hou et al. (2015) is motivated from a general equilibrium theory that links firm investments to consumption, but the theory does not imply a factor model directly (Lin and Zhang 2013).

[4] Since most implied cost of capital identify expected returns as the roots that satisfies the assumed valuation model for a given firm-period, expected returns are not identified without these assumptions.

The most commonly adopted valuation model for accounting-based expected returns is the residual income (or abnormal earnings) valuation (RIV) model (Claus and Thomas 2001; Gebhardt et al. 2001; Easton et al. 2002; Pástor et al. 2008; Nekrasov and Ogneva 2011). Peasnell (1982) and Ohlson (1995) show that, given clean surplus accounting and an arbitrage-free market, the market price of equity P_t is equal to the book value of equity b_t plus the present values of discounted future abnormal earnings:

$$P_t = b_t + \sum_{j=1}^{\infty} \frac{\mathbb{E}_t[x^a_{t+j}]}{(1+r)^j} \tag{2.1}$$

where the expected returns $r_t = r$ for all t. Note that abnormal earnings $x^a_{t+j} = x_{t+j} - r\mathrm{b}_{t+j-1}$ are also functions of the discount rate r.

Ohlson and Juettner-Nauroth (2005) show that an equivalent abnormal earnings growth (AEG) valuation model that highlights the relation between market value and earnings and earnings growth can be derived as

$$P_t = \frac{1}{r}\,\mathbb{E}_t[x_{t+1} + \sum_{j=2}^{\infty} \frac{g^a_{t+j}}{(1+r)^{j-1}}] \tag{2.2}$$

where $g^a_{t+j} = x_{t+j} + rd_{t+j-1} - rE_{t+j-1}$ defines the abnormal earnings growth. Gode and Mohanram (2003) and Easton (2004) apply different versions of the AEG model to infer expected returns.

Once one can find reasonable proxies for the expectational inputs and make reasonable assumptions about the post-horizon behavior of relevant constructs, the expected return, or implied cost of capital, r can be readily identified by numerically solving the above models.

Although ICC models have the merit of being virtually free of assumptions about the accounting data generating processes,[5] an ICC model by definition identifies a single constant expected return estimate for all future horizons, which mostly captures average long-run expected returns. Given that expected returns predictably vary over time (Cochrane 2009, 2011), the relation between constant expected return estimates and the true conditional expectations of next-period realized returns is distorted (Hughes et al. 2009). Pástor et al. (2008) also elaborate on this issue and suggest more forcefully that realized returns are likely to be negatively correlated with temporal changes in long-run expected returns, leaving the relation between ICC estimates and one-period realized returns to be weak . Note that the issue with constancy of expected return cannot be solved by simply indexing r with a time subscript, even if such *ad hoc* adjusted expected returns can be identified with sufficient data. When the economy is characterized by risk averse investors and stochastic risk premiums, a stochastic discount factor (SDF) or state-space valuation technique must be used, and the definition of abnormal earnings or abnormal earnings growth must also be adapted (Feltham and Ohlson 1999; Ang and Liu 2001).[6] The new approach proposed in this study is able to identify expected one-period-ahead returns while allowing conditional expectations to vary over different forward horizons.

Another important unique feature of the new approach is that it does not rely on arbitrary assumptions about terminal growth rates or dividend policies. Naturally, RIV or AEG models involve discounting an infinite series of future payoffs to equate the current stock price, but this necessarily requires truncation at a given point in the future. Researchers must then supply some explicit assumptions about the growth in the payoff measures (e.g. abnormal earnings or abnormal earnings growth) post the truncation point. In addition, while

[5]RIV requires only the no-arbitrage condition and clean-surplus accounting to hold, and AEG holds even without clean surplus accounting.

[6]Specifically, the r in the definitions of x_t^a and g_t^a are to be replaced with risk-free rates when the stochastic discount factor or state-space valuation technique is used.

leading valuation models have the dividend irrelevance property, practical applications must still involve arbitrary assumptions about dividend policies to enable forecasting future series of earnings and/or book values. My approach summarizes the valuation implications of future earnings growth and book values into the implied 'other information' term and estimates the stochastic parameters of this other information term from the data, thus it avoids making such questionable assumptions.

2.2.3 Characteristics-based models

Recently, Lyle et al. (2013), Lewellen et al. (2015), Lyle and Wang (2015) and Penman and Zhu (2017) have proposed a characteristics-based approach towards estimating expected returns. While motivated by different arguments and implemented in different ways, these models estimate the predictive relations between firm characteristics and future returns from historical data, and apply the estimates to current characteristics to capture forward-looking expected returns. It appears that this approach has claimed some success in predicting a meaningful fraction of the variation in realized returns (Lee et al. 2015). However, except for and Lyle et al. (2013) and Lyle and Wang (2015), the choice of firm characteristics in these models are based almost purely on empirical explorations, without clear theoretical guidance.

In addition, the implementations of characteristics-based models still rely on noisy realized returns. Thus, the approach is not genuinely forward-looking, and shares some of the same issues associated with using realized returns as faced by methods based on factor models.[7]

Furthermore, it is often unclear *a priori* why the predictive power of firm characteristics for stock returns is due to risk rather than mispricing. In principle,

[7]Admittedly, the predictive relations between firm characteristics and future returns appear more stable than those between stock returns and common risk factors (Lewellen et al. 2015). Thus, the characteristics-based expected return estimates perform better out-of-sample when compared with factor model estimates.

it seems plausible that firm characteristics proxy for firm-level exposure to common risk factors. For instance, Fama and French (1992) suggest that the book-to-market ratio predicts returns because it proxies for the firm's factor betas, however, this conjecture has not been conclusively tested. Chapter 3 of this thesis uses a novel testing methodology and shows that the return predictive ability of many firm characteristics is not explained by their association with firm exposure to common risk factors. Furthermore, Bartram and Grinblatt (2017) construct a 'mispricing' signal by taking the difference between market prices and statistically optimal valuations, which predicts economically large and statistically significant abnormal returns. These abnormal returns are *ex ante* predictable, but they are derived from a process that purposefully searches for statistically 'wrong' prices, which is hard to be reconciled with the view that statistically predictable returns are all due to risk.

Admittedly, one may argue that expected returns can be defined as returns that are *ex ante* predictable, and whether they are driven by mispricing is irrelevant. While this is a valid point if one views expected returns as a statistical concept and if the purpose is to build optimal trading strategies, this view does not speak to the economic question: *What is the market expectation?* In other words, the returns that investors expect to earn may deviate from optimal statistical forecasts. For research settings that examine investors' information processing behavior, which is central to the accounting literature, the market expectation view is more important than the statistical view. The new approach introduced in the current study takes the former view.

I also find similarities between the new approach and some leading characteristics-based models. For instance, Penman and Zhu (2017) also express expected returns as a linear function of earnings yield and book-to-market ratio, adjusted for a vector of variables that are empirically shown to predict earnings growth. The underlying argument is that variables that forecast earnings growth imply fundamental risk beyond earnings and book values. In comparison, my model adjusts earnings yield and book-to-market by implied other information.

This other information term is supposed to capture the net present values of business activities that are not recognized in the current accounting information but that will eventually feed back into future earnings and book values when they materialize. Thus, the implied other information term is naturally related to expected growth, consistent with the spirit of Penman and Zhu (2017).[8] In this vein, one can interpret the growth component in Penman and Zhu (2017) as a specialized parametric representation of my implied other information term.

2.3 Theoretical development

The seminal studies by Ohlson (1995) and Feltham and Ohlson (1995) establish a linear relation between the market value of equity and *current* accounting data, instead of expected future values. However, these studies are based on a setting characterized by risk-neutral investors and constant discount rates, limiting their applications to empirical work. Feltham and Ohlson (1999) and Gode and Ohlson (2004) show that the linear relation also holds in more general settings with risk aversion and stochastic interest rates. However, for the purpose of capturing firm-level stochastic expected returns[9], it is important to allow for risks and thus risk premiums to vary over time.

I generalize the linear pricing rule developed in Ohlson (1995) and Feltham and Ohlson (1995) to a market with risk-averse investors, linear information dynamics, and stochastic volatility in firm fundamentals. This setting admits time-varying expected returns through the correlation between accounting data and the stochastic aggregate consumption growth. My modeling

[8]This is also consistent with Ohlson's (1995) original description of other information in that any priced information must materialize in the form of incremental future abnormal earnings.

[9]In this thesis, I use the words 'expected return' and 'discount rate' interchangeably.

approach follows that of Ang and Liu (2001) and relies on the risk-neutral pricing technique based on stochastic discount factors instead of explicit expected returns.[10] Given that a model based on stochastic discount factors is equivalent to a model based on expected returns, there is no loss from adopting this approach.

2.3.1 Generalized accounting-based valuation models

Consider a discrete-time setting with infinite horizon. Let $t = 1, 2, \ldots, \infty$ denote points in time at which market activities (i.e. trading, dividend payments, and releases of accounting data) take place. The usual condition of filtration applies, meaning that any variable Z_{t-l} ($l \geq 0$) measurable with respect to time $t - l$ information algebra is also measurable with respect to time t information: $\mathbb{E}_t[Z_{t-l}] = Z_{t-l}$, where $\mathbb{E}_t[\cdot]$ is the expectation operator conditional on date-t information available to the market.

I start by assuming the existence of a representative investor and a tractable form of her utility function.

Assumption 1. *There exists a representative investor characterized by a time-additive and constant relative risk aversion (CRRA) utility function*

$$U_t(C_{j=1}^{\infty}) = k^j \frac{1}{1-\rho} C_{t+j}^{1-\rho} \tag{2.3}$$

where $k \in (0, 1)$ is the impatience parameter, and $\rho \in (1, +\infty)$ is the coefficient of relative risk aversion. $C_{j=t}^{\infty} > 0$ denotes the sequence of current and future consumptions with C_j representing the consumption at date j.

[10] Here, the term 'risk-neutral pricing' does not mean that investors are risk-neutral. Instead it refers to a valuation technique where the price is represented by the risk-neutral price plus certain risk adjustment.

The existence of a representative investor simplifies my subsequent analysis by reducing the derivation of the competitive equilibrium price to characterizing the first-order conditions of a single investor's portfolio decisions.[11] Next, I introduce the following definition that is central to the subsequent analysis.

Definition 1. *A stochastic process $m_{t=1}^{\infty}$ is a stochastic discount factor (SDF) process if it satisfies*

$$m_t P_t = \mathbb{E}_t[m_{t+1}(P_{t+1} + d_{t+1})] \tag{2.4}$$

for all $t = 0, 1, 2, \ldots$, where P_t denotes the date-t price of any asset traded in the market and d_t is the cash distribution from the asset at date t. $\mathbb{E}_t[\cdot]$ is the expectation operator conditional on date-t information. m_t is the stochastic discount factor (SDF) at date t.

The conditional expectations of SDFs are reflected in the periodical risk-free rates. Specifically, consider a bond initiated at date t with a constant (risk-free) date-$t+1$ payoff of 1. Since equation (2.4) applies to all assets, the price of the bond at date t is $E_t[\frac{m_{t+1}}{m_t}]$. Thus the risk-free rate over the period from t to $t+1$ is $R_t^f = 1/E_t[\frac{m_{t+1}}{m_t}] = m_t/E_t[m_{t+1}]$. The subscript t in R_t^f indicates that it is measurable with respect to date-t information. However, R_t^f may not be a global constant, it remains unknown prior to t in general.

Assumption 1 implies that the market is free of arbitrage, which is assumed by all previous studies in this literature. According to the *Fundamental Theorem of Asset Pricing*[12], the market is free of arbitrage if, and only if, there exists a *strictly positive* SDF process. Given Assumption 1, the first-order condition of the representative investor's portfolio decision is given by the Euler

[11] The existence of a representative investor requires that the competitive equilibrium in the market is Pareto optimal. This is satisfied if all investors have linear risk tolerance with the same cautiousness parameter. See Chapter 7 of Back (2017) for details.

[12] See, for example, Duffie (2010).

equation:

$$P_t C_t^{-\rho} = \mathbb{E}_t[k C_{t+1}^{-\rho}(P_{t+1} + d_{t+1})] \Leftrightarrow P_t = \mathbb{E}_t[k \frac{C_{t+1}^{-\rho}}{C_t^{-\rho}}(P_{t+1} + d_{t+1})] \qquad (2.5)$$

Equation (2.5) must hold for all assets. Hence, the process with $\frac{m_{t+1}}{m_t} = k(\frac{C_{t+1}}{C_t})^{-\rho}$ is an SDF. Since k and C_j are strictly positive, this implies that the market is free of arbitrage, as claimed. In this chapter, I use this particular form of SDF process for all valuation analysis.[13]

In fact, for the purpose of this study, the specific form of $m_{t=1}^{\infty}$ does not bear critical importance and other positive SDF processes can be consistent with my subsequent analyses. In this sense, Assumption 1 is stronger than needed, but it anchors the model on a concrete variable (i.e. consumption) so that the stochastic properties of the SDF process can be motivated in terms of that variable.

My second assumption rules out the possibility of 'bubbles' by imposing a transversality condition. This assumption ensures that the price of any asset is well defined and bounded.

Assumption 2. *The transversality condition holds*

$$\mathbb{E}_t[m_T P_T] \to 0 \quad as \quad T \to \infty \qquad (2.6)$$

Equation (2.4) and Assumption 2 together imply the generalized version of the dividend discount model (DDM). First iterate equation (2.4) forward to a finite horizon $T > t$ and apply the law of iterated expectations:

[13] If the market is incomplete, which is plausible in reality, then infinitely many SDF processes may exist. However, the differences between alternative SDF processes have no valuation implications.

$$m_t P_t = \sum_{j=1}^{T} \mathbb{E}_t[m_{t+j} d_{t+j}] + \mathbb{E}_t[m_T P_T] \quad (2.7)$$

Taking the limit $T \to \infty$ and applying Assumption 2 yield

$$P_t = \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} d_{t+j}] \quad (2.8)$$

as claimed. Building on the generalized DDM of equation (2.8) and the transversality condition in Assumption 2, one can obtain a generalized version of Ohlson and Juettner-Nauroth's (2005) abnormal earnings growth (AEG) valuation model. I state this result in the following proposition.

Proposition 1. *For any strictly positive SDF process $m_{t=1}^{\infty}$, given Assumptions 2, the market price of the asset is*

$$P_t = \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} x_{t+1}] + \sum_{j=2}^{\infty} \sum_{s=j}^{\infty} \mathbb{E}_t[\frac{m_{t+s}}{m_t} g^a_{t+j}]$$

where $g^a_{t+j} = \Delta x_{t+j} - (R^f_{t+s-1} - 1)(x_{t+j-1} - d_{t+j-1})$.

The first term in Proposition 1 represents capitalized one-period-ahead earnings, and the second term captures market valuation of future 'abnormal earnings growth' (in dollars). Note, however, that the definition of g^a_{t+j} is different from that in Ohlson and Juettner-Nauroth (2005) in that I replace the discount rate with spot risk-free rates. This replacement is necessary when the discount rate is no longer assumed to be constant. See Appendix A for the proof of Proposition 1.

Notably, the procedure for proving Proposition 1 does not involve any assumption based on the characteristics of accounting data involved (i.e. earnings). The key step is to replace dividends with the simple identity $d_t = x_t - (x_t - d_t)$, but there is no restriction on how earnings x_t should be generated. Therefore, the same expression can be obtained if x_t is replaced with any other *arbitrary* variable. This suggests that AEG valuation does not depend on the measurement of earnings.

The following corollary shows that Proposition 1 holds Ohlson and Juettner-Nauroth's (2005) version as a special case.

Corollary 1. *If* $\frac{m_{t+j}}{m_t} = R^{-j}$*, where* $R \in (1, \infty)$ *is a constant known at date* t*, then*

$$P_t = \frac{1}{R-1}\,\mathbb{E}_t[x_{t+1}] + \frac{1}{R-1}\sum_{j=2}^{\infty}[\Delta x_{t+j} - (R-1)(x_{t+j-1} - d_{t+j-1})] \qquad (2.9)$$

The proof of Corollary 1 is straightforward. Starting from Proposition 1, one can reverse the procedure of the proof of Proposition 1 to obtain $P_t = \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t}(x_{t+1} + \sum_{k=2}^{j} \Delta x_{t+k})] - \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t}(x_{t+j} - d_{t+j})]$ and then substitute in $\frac{m_{t+j}}{m_t} = R^{-j}$ to obtain Corollary 1. The details are omitted because they are largely repetitive.

Similarly, one can also derive a generalized version of the RIV model, with an additional assumption that accounting data satisfy the clean surplus relation.[14]

Assumption 3. *The clean surplus relation holds*

$$b_t + x_{t+1} - d_{t+1} = b_{t+1} \qquad (2.10)$$

[14] The derivation of a similar generalized RIV model first appears in Feltham and Ohlson (1999) in a finite-horizon finite-state setting using static Arrow-Debreu prices. The model presented in Proposition 2 slightly generalizes Feltham and Ohlson (1999) to an infinite horizon by transversality condition and to continuous state space by adopting a more general SDF approach.

where b_t, x_t and d_t are the book value of equity, earnings and dividends of the firm at date t,

Proposition 2. *For any strictly positive SDF process $m_{t=1}^{\infty}$, given Assumptions 2 and 3, the market price of the asset*

$$P_t = b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} x^a_{t+j}] \tag{2.11}$$

where $x^a_{t+j} = x_{t+j} - (R^f_{t+j-1} - 1)b_{t+j-1}$.

Proposition 2 shows that the market price is equal to the book value plus future "abnormal earnings" discounted by the SDFs. The definition of abnormal earnings is different from those used in most empirical implementations, where the risk-free rates R^f_{t+j-1} are replaced by risk-adjusted expected returns. The replacement is valid as long as the risk-adjusted expected return and risk-free rates are assumed to be constant over time, but once the constancy assumption is dropped, such adjustment for risk is no longer appropriate (Ang and Liu 2001; Callen 2016). Proposition 2 is proved in Appendix A.

In fact, a similar model can be derived without Assumption 3, which does not strictly hold under GAAP accounting. To achieve this, one can define an alternative non-GAAP measure of 'earnings' $x^*_t = \Delta b_t + d_t$, then Proposition 2 follows if x^*_t replaces x_t. However, one can easily confirm by checking the proof above that the measurement of book value b_t is not restricted at all. Therefore, like in the case of AEG, this again suggests that accounting measurement does not affect RIV valuation as long as earnings can be redifined to equate book value growth plus dividends. This point is first emphasized in Ohlson (2005a) in a constant expected return setting.

The following corollary confirms that Proposition 2 holds RIV models of constant discount rates as a special case. The proof is very similar to that sketched for Corollary 1 and thus not outlined here.

Corollary 2. *If* $\frac{m_{t+j}}{m_t} = R^{-j}$*, where* $R \in (1, \infty)$ *is a constant known at date* t*, and if Assumption 3 holds, then*

$$P_t = b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[R^{-j}(x_{t+j} - (R-1)b_{t+j-1}] \tag{2.12}$$

The analyses in this subsection show that the RIV and AEG models are equivalent to DDM in the generalized setting. The results highlight the weak nature of these models in the sense that they do not incorporate the underlying data generating processes of the accounting numbers. In other words, these models suggest that equity valuation can be "neutral" to how accounting is done. There is no theoretical imperative regarding whether accounting numbers should be used for valuation instead of dividends.

Hence, the important question is *Why should one attempt accounting-based valuation at all?* It is well known that dividends are difficult to predict (Cochrane 2009), so the expectational terms in the DDM are too speculative as inputs for valuation purposes. Essentially, RIV and AEG address this difficulty by replacing future dividends with some accounting-based payoff measures (abnormal earnings, earnings and/or abnormal earnings growth), but one can argue that since RIV- or AEG-type models can be developed with arbitrarily measured variables, the gain from using accounting-based valuation is not *ex ante* clear. Therefore, the real benefit, if any, of using accounting data for valuation must be related to how the accounting system allows the expectational terms in the valuation model to be better anchored on *current* information. This is analyzed in the next section.

2.3.2 Linear information dynamics and a generalized linear pricing rule

As is discussed in the previous section, accounting-based valuation is useful only to the extent that *expected* future accounting-based payoff measures can be meaningfully anchored on *current* information. Connecting market value to current accounting data requires explicit modelling of the accounting data generating process. Ohlson (1995) and Feltham and Ohlson (1995) first supply such a connection in the risk-neutral, constant interest rate setting with first-order autoregressive linear information dynamics. They show that the market value is a linear function of current earnings, book value, dividends and another term representing 'other information' not captured by these three accounting numbers. This linear pricing rule has been generalized to market settings with risk aversion (Feltham and Ohlson 1999; Ang and Liu 2001), stochastic interest rates (Ang and Liu 2001; Gode and Ohlson 2004) and aggregate risk dynamics (Lyle et al. 2013). In addition, prior studies have also made robust the linear pricing rule under various alternative forms of information dynamics with AR(q) with $q > 1$ (Callen and Morel 2001), allowance for the predictive role of dividends (Clubb 2013), and affine abnormal earnings processes (Lyle et al. 2013).

I start by assuming a parametric form of the information dynamics of a vector of firm fundamentals that drive equity valuation. Similar to Ohlson (1995), I specify a two-variable first-order vector autoregressive (VAR(1)) model for abnormal earnings x_t^a and a term representing other predictive information v_t that forecasts abnormal earnings. This two-variable setting is not constraining. For instance, if one argues that accounting numbers other than abnormal earnings (e.g. accruals, investment) should also be specified in the model, then the v_t may be viewed as a unobserved stochastic term plus a linear combination of these identified accounting numbers with time-varying coefficients. Therefore, this specification can hold any expanded definition of X_t as a special case. Conveniently, this assumption connects to the generalized RIV model in Proposition 2 as the machinery for my subsequent analysis.

Assumption 4. *There are two firm fundamental variables that determine equity valuation, and they follow a first-order Gaussian vector autoregressive process*

$$x^a_{t+1} = \omega^{(t)} x^a_t + v_t + \epsilon_{1,t+1}$$
$$v_{t+1} = \phi^{(t)} v_t + \epsilon_{2,t+1}$$

with $\omega \in (0, 1)$ *and* $\phi > 0$*. Equivalently in vector-matrix notation,*

$$X_{t+1} = \mathbf{\Phi}^{(t)}_t + \epsilon_{t+1} \tag{2.13}$$

where

$$X_t = \begin{bmatrix} x^a_t \\ v_t \end{bmatrix}, \quad \mathbf{\Phi}^{(t)} = \begin{bmatrix} \omega^{(t)} & 1 \\ \phi^{(t)} & 0 \end{bmatrix}, \quad \textit{and} \ \epsilon_{t+1} = \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \end{bmatrix}.$$

The VAR coefficients $\Phi^{(t)}$ *are assumed to be deterministic, independent of* X_t*, and does not vary over forward horizons, but they are updated at each date* t*. I further make a technical assumption that* $\omega^{(t)} > R^f_t$ *or* $\phi^{(t)} > R^f_t$ *can hold for only finitely many dates* t*. This ensures that the infinite sum of present values of future abnormal earnings is well defined for each date* t*.*

The random vector $\epsilon_{t+1} \sim N(0, \Sigma_t)$*, and its covariance matrix* Σ_t *is positive definite and satisfies*

$$\Sigma_t = \mathbf{D} \otimes X_t = \mathbf{D}_1 x^a_t + \mathbf{D}_2 v_t, \tag{2.14}$$

where the matrices $\mathbf{D}_1$, $\mathbf{D}_2$ *are constant and* 2×2 *symmetric. The symbol* $\otimes$ *represents the tensor product operator.*

It is worth noting that Assumption 4 differs in several ways from the information dynamics in Ohlson (1995) and many other studies in the literature. First, VAR coefficients $\Phi^{(t)}$ are allowed to depend on date t information, but they are known constants at date t. $\Phi^{(t)}$ is assumed to be deterministic so that there is no learning uncertainty, and it does not vary over forward horizons, suggesting the same $\Phi^{(t)}$ applies to all future dates $t+j$ ($j \geq 1$) when expectation is taken with respect to date t information. This is a generalization of constant coefficient linear dynamics models because realistically investors' beliefs are likely to respond to new information over time (Pastor and Veronesi 2009).[15] While it is possible to explicitly model the dependence of $\Phi^{(t)}$ on t, this is not necessary for the purpose of this study. Second, the shocks to abnormal earnings and other predictive information are heteroskedastic, as their covariance matrix scales with the level of X_t through the tensor product operation.[16]

The previous section identifies that a valid SDF process is determined by intertemporal growth in aggregate consumption, given recursively as $\frac{m_{t+1}}{m_t} = k(\frac{C_{t+1}}{C_t})^{-\rho}$. I utilize this form of SDF process to derive the valuation model. Under the RIV framework, the difference between market value and book value is determined by the inner products (defined as conditional expectations) of future abnormal earnings and SDFs. Hence, it is necessary to model the co-movement of the SDFs and firm fundamentals X_t. Without loss of generality, I decompose consumption growth C_{t+1}/C_t into three conditionally independent, log-normal elements, such that the first element is log-linear in firm fundamentals, the second perfectly correlates with the shocks to firm fundamentals ϵ_{t+1}, and the third is orthogonal to ϵ_{t+1} and X_t .

[15]However, I do not incorporate forward-looking model uncertainty in this study to simplify the analysis. See Callen (2016) for an example on how the linear pricing rule holds after incorporating forward-looking model uncertainty.

[16]Note that the covariance matrix Σ_t remains symmetric as long as the matrices $\mathbf{D}_1$, $\mathbf{D}_2$ are symmetric. I do not specify the specific forms of $\mathbf{D}_1$ or $\mathbf{D}_2$.

Assumption 5. *The aggregate consumption growth C_{t+1}/C_t is log-normally distributed conditional on date t information*

$$z_{t+1} := log(C_{t+1}/C_t) = \delta' X_t + \gamma' \epsilon_{t+1} + \eta_{t+1}$$

where

$$\eta_{t+1} = \lambda \eta_t + (1 - \lambda)\bar{C} + e_{t+1}$$

with

$$e_{t+1} \sim N(0, \sigma_\eta^2)$$

and η_{t+1} is independent of X_t and ϵ_{t+1}.

Assumption 5 specifies that the consumption growth is driven by a normally distributed latent process $z_{t=1}^{\infty}$, which is in turn driven by two independent processes. The first process can be interpreted as the orthogonal projection of aggregate consumption growth onto the space spanned by the shocks to firm fundamentals, and the second is a random process not reflected by firm fundamentals. Intuitively, the shocks to aggregate consumption are partially reflected in shocks to firm fundamentals, consistent with the notion that firm fundamentals carry macroeconomic news. However, the changes in aggregate consumption are unlikely to be fully manifested in firm-level news, as consumption is determined by the general equilibrium across all sectors of the economy. The log-normal structure is motivated by the fact that consumption is not allowed to be negative and that log-normal consumption produces results that exactly hold in continuous time without any distributional assumption (Cochrane 2009; Back 2017).

Finally, I follow Ang and Liu (2001) and assume that the interest rate process is independent of the process of firm fundamentals (i.e. abnormal earnings x_t^a and its predictor v_t). While R_t^f enters negatively to the definition of x_{t+1}^a as the 'capital charge', a change in interest rate should also lead to an opposite change in the yields of existing firm investments and thus earnings, offsetting the former effect. To see this point, rewrite the definition of abnormal earnings as $x_{t+1}^a = [ROE_{t+1} - (R_t^f - 1)]b_t$, where $ROE_{t+1} = x_{t+1}/b_t$ is the accounting return on equity for the period t to $t+1$. As a benchmark case, if an increase in the interest rate corresponds to a one-to-one increase in ROE then abnormal earnings will not be affected (Nissim and Penman 2003). Of course, this relation is not expected to hold exactly due to, for example, conservative accounting recognition and the feedback effect on firm investments, and how the association between R_t^f and ROE_{t+1} deviate from the benchmark case is unclear.[17] I maintain this assumption as a reasonable first approximation.

Technically, given Assumption 5, the date-t interest rate is determined as

$$\begin{aligned} R_t^f &= \frac{1}{\mathbb{E}_t[\frac{m_{t+1}}{m_t}]} \\ &= \frac{1}{k}\exp\{\rho(\delta' X_t + \lambda\eta_t + (1-\lambda)\bar{C}) - \frac{1}{2}\rho^2(\gamma'\Sigma_t\gamma + \sigma_\eta^2)\} \end{aligned}$$

For the interest rate to be independent of firm fundamentals, the terms $\rho\delta' X_t$ and $-\frac{1}{2}\rho^2\gamma'\Sigma_t\gamma$ must offset to zero because they both depend on X_t (note that $\Sigma_t = \mathbf{D} \otimes X_t$).

Assumption 6. *The interest rate process is independent of the process of the*

[17]Nissim and Penman (2003) find that empirically a unit increase in R_t^f leads to 0.84 unit increase in ROE_{t+1} on average, and the coefficient is not statistically distinguishable from one as computed using their reported estimates.

firm fundamentals. This implies

$$\delta' X_t = \frac{1}{2}\gamma'\Sigma_t\gamma$$

and thus

$$R_t^f = \frac{1}{k}\exp\{\lambda\eta_t + (1-\lambda)\bar{C} - \frac{1}{2}\rho^2\sigma_\eta^2\}$$

With Assumptions 1 to 6, one can establish the following proposition, which shows that the linear relation between the market value and current firm fundamentals is preserved.

Proposition 3. *Given Assumptions 1 to 5, the market value of equity is linear in firm fundamentals*

$$\begin{aligned} P_t &= b_t + \alpha_t x_t^a + \beta_t v_t \\ &= b_t + \alpha_t x_t^a + \vartheta_t \end{aligned}$$

where α_t *and* β_t *are measurable with respect to date* t *information, and* ϑ_t *is defined in the second equality. Or equivalently,*

$$P_t = (1+\alpha_{1t})b_t + \alpha_{2t}x_t + \alpha_{1t}d_t + \vartheta_t$$

where $\alpha_{1t} = -\alpha_t(R_{t-1}^f - 1)$*,* $\alpha_{2t} = \alpha_t$

As in Ohlson (1995) (Equation (5), p. 669), this expression implies that the market value equals book value adjusted for current abnormal earnings and 'other information' that forecasts future abnormal earnings. The empirical content of such 'other information' term is not explicitly specified.

Poposition 3 highlights the robustness of the linear pricing rule (Ohlson 1995; Feltham and Ohlson 1999; Pope and Wang 2005). It survives in a market environment with dynamic risk and stochastic firm-level and economy-wide volatility.[18] Furthermore, the generalization is applicable to any other alternative linear information dynamics. For instance, Clubb (2013) specifies an alternative VAR process by replacing v_t with book value and dividends and imposing several restrictions on the auto-regressive coefficients. Maintaining all other assumptions, one can show that the market value is a linear form in current abnormal earnings, book value and dividends. The book value assumes a valuation weight greater than one and the dividend receives a positive weight because it forecasts future abnormal earnings.

The most important feature of the linear pricing rule in Proposition 3 is that the linear valuation coefficients are stochastic. This feature arises from two sources. First, the interest rates are stochastic, leading to different discounting and pricing of firm fundamentals over time. Ang and Liu (2001) and Gode and Ohlson (2004) consider this effect, while they leave the interest rate process unspecified. My approach of tying SDFs to the aggregate consumption process allows me to identify the exact process of interest rates.[19] Second, the VAR coefficients $\Phi^{(t)}$ are formed and updated at each date t, so the *forecasting* implications of current firm fundamentals vary over time, and such time-varying predictive value translates into time-varying valuation weights. Proposition 3 is proved in Appendix A.

Lyle et al. (2013) derive a similar linear pricing rule in a market with dynamic aggregate risk.[20] Proposition 3 is distinguished from their model in several aspects. First, the source of underlying dynamic risk in Proposition 3 is the stochastic volatility in the firm fundamentals and thus their time-varying comovements with aggregate consumption, whereas Lyle et al. (2013) models

[18]By economy-wide volatility, I implicitly refer to consumption growth volatility. However, as I noted in the previous section, alternative specification of the SDF process or the representative investor's utility function should warrant the same analyses and results.

[19]I do not explicitly present the parametric term structure model of interest rates because it is not of central interest to this study.

[20]in comparable notations, the Lyle et al. (2013) model is $P_t = b_t + \alpha x_t^a + \beta v_t - \gamma \sigma_{m,t}$, where $\sigma_{m,t}$ is the aggregate risk factor and γ is the coefficient of the firm's exposure to aggregate risk. Therefore, $\gamma \sigma_{m,t}$ can be interpreted as a risk adjustment term.

risk dynamics through innovations in an aggregate risk factor (i.e. aggregate return volatility) while holding co-movements constant over time. In addition, my model substitutes conditional covariances with a linear function of state variables X_t, thus muting the appearance of an explicit risk adjustment in the pricing formula. This is an important difference because, empirical estimations of covariance risk adjustments are notoriously difficult.

Notably, the 'other information' term ϑ_t in Proposition 3 is not equal to the 'other information' term v_t in Assumption 4. It is equal to the market value attributed to the future growth in abnormal earnings, beyond what is captured by current book value and abnormal earnings. In other words, its valuation relevance relies on its ability to forecast future abnormal earnings. Hence, the content of 'other information' is necessarily expectational, which complements transactions-based accounting data that in principle are purged of speculative values.

Intuitively, this other information term is supposed to capture the net present values of business activities that are not recognized in the current accounting information but that will eventually feed back into future earnings and book values when they materialize. Thus, other information ϑ_t is naturally related to expected growth. The following claim shows that the transformed 'other information' term ϑ_t preserves AR(1) property, which will be useful for subsequent derivations.

Claim 1. *The transformed 'other information' term follows an AR(1) process*

$$\vartheta_{t+1} = \varphi_t \vartheta_t + \epsilon_{\vartheta,t+1}$$

where $\varphi_t = \frac{\phi^{(t)}\,\mathbb{E}_t[\beta_{t+1}]}{\beta_t}$.

Proof is given in Appendix A. The claim shows that the persistence of 'other information' in the linear pricing rule φ_t is scaled by the ratio of expected to current valuation coefficients on other information in the VAR structure $\mathbb{E}_t[\beta_{t+1}]/\beta_t$, which depends on the local term structure of interest rate. Depending on the magnitude of this ratio relative to $\phi^{(t)}$, φ_t may exceed or fall below one. In other words, 'other information' in the linear pricing rule may grow as well as decay in expectation.

So far, the analyses in this subsection have used the generalized RIV as the machinery. However, RIV is not central to the derivation of the generalized linear pricing rule. As Ohlson (2001) and Ohlson (2005a) point out, the same results can be obtained through working with the DDM or AEG,[21] given clean surplus accounting (Assumption 3) guarantees their equivalence with RIV.[22] In essence, the linear information dynamics (Assumption 4) can be translated to an equivalent set of restrictions on dividends or abnormal earnings growth. Hence, working with the RIV machinery itself is not a restriction.

2.3.3 Identifying one-period-ahead expected returns

In this subsection, I utilize the generalized linear pricing rule to derive an empirically implementable expression for the *one-period-ahead* expected return. Specifically, I show that the one-period-ahead expected return can be identified as a linear combination of forward earnings yield, book-to-market ratio and an estimate of model implied other information. I emphasize the focus on *one-period-ahead* expected returns to distinguish from the ICC literature, which makes no distinction between expected returns over different horizons (i.e. no assumed term structure of expected returns). While it is widely acknowledged that expected returns vary over time, a forward-looking measure of expected return that genuinely allows for a term structure still does not

[21] Note that, strictly speaking, Ohlson (2001) and Ohlson (2005a) discuss the cases with constant expected returns, but the spirit of these points carries forward to the generalized case analyzed above.

[22] Of course, as previously discussed, AEG is subject to weaker theoretical restrictions because it does not depend on clean-surplus accounting. However, in the environment described in this study, where the clean-surplus relation is assumed to hold, RIV is equivalent to AEG.

exist.[23] In the model described in this chapter, term-structural variations in expected returns have two sources: (1) the term structure of interest rates $(R^f_{t+j})^{\infty}_{j=1}$ and (2) the stochastic volatility $\mathbf{\Sigma}_t = \mathbf{D} \otimes X_t$ of firm fundamentals and thus the time-varying covariances of firm fundamentals with aggregate consumption growth. To simplify the analysis and reduce the empirical challenge for model identification, I assume interest rates are flat over time. This implies that the linear valuation parameters in Proposition 3 do not vary predictably: $\mathbb{E}_t[\alpha_t] = \alpha_t$ and $\mathbb{E}_t[\beta_t] = \beta_t$ are zero.

Another important feature that sets the new approach apart from ICC models is that I explicitly estimate other information implied by the linear pricing rule to construct the measure of one-period-ahead expected return. In finite horizon applications, it is unlikely that all valuation implications can be captured by current book value and abnormal earnings, so incorporating a measure of other information is potentially important. Indeed, Dechow et al. (1999) use an approach suggested by Ohlson (2001) to estimate other information and show that incorporating other information estimates significantly improves the explanatory power of the linear pricing rule for price levels. Choi et al. (2006) further refine the approach to allow for conservatism bias in accounting-based valuation. In ICC models that rely on RIV or AEG, researchers must rely on arbitrary assumptions about dividend policies and growth rates in terminal valuations to identify expected returns.[24] By implementing the linear pricing rule in Proposition 3 and estimating the model implied other information, I avoid making such assumptions. Of course, the absence of these assumptions is a consequence of stronger theoretical restrictions required for Proposition 3, and whether imposing these restrictions is superior to making explicit growth

[23] Several studies in the finance literature attempt to model and estimate the term structure of expected returns at both market and firm levels (e.g. Kelly and Pruitt 2013; Lyle and Wang 2015), but their approaches rely on historical rather than forward-looking data.

[24] Easton et al. (2002) and Nekrasov and Ogneva (2011) are two exceptional studies that estimate, rather than assume, terminal growth rates. However, they still rely on explicit dividend policy assumptions. While dividend policies should be irrelevant for both RIV and AEG (Ohlson 1995; Ohlson and Juettner-Nauroth 2005), their empirical implementations with finite horizons must still explicitly make assumptions about dividends. The extent to which ICC estimates are sensitive to dividend assumptions is yet to be examined.

and dividend assumptions is an empirical question.

To reduce notational burden, I suppress time subscripts hereafter. I start with Proposition 3 and Claim 1:

$$P_t = (1 + \alpha_1)b_t + \alpha_2 x_t + \alpha_1 d_t + \vartheta_t \tag{2.15}$$

where ϑ_t follows the following process

$$\vartheta_{t+1} = \phi\vartheta_t + \epsilon_{\vartheta,t+1} \tag{2.16}$$

With these structures in place, the no-arbitrage condition relates prices at dates t and $t+1$ through the one period-ahead expected return ER_t as:

$$ER_t \times P_t = \mathbb{E}_t[P_{t+1} + d_{t+1}] \tag{2.17}$$

After expanding the right-hand-side using the linear pricing rule and applying the clean-surplus relation, I obtain

$$ER_t = (1 + \alpha_1 + \alpha_2)\frac{\mathbb{E}_t[x_{t+1}]}{P_t} + (1 + \alpha_1)\frac{b_t}{P_t} + \phi\frac{\vartheta_t}{P_t} \tag{2.18}$$

Equation (2.18) implies that one-period-ahead return is a linear function of book-to-market ratio, next-period earnings yield, and the price-deflated 'other information' term. To construct an expected return measure from this equation, one requires a set of parameter estimates (α_1, α_2 and ϕ) and a proxy for the 'other information' ϑ_t.

I pursue a forward-looking approach to obtaining the parameter estimates using the method developed in Ashton and Wang (2013). The estimation procedure can be summarized in three steps. First, I estimate the model parameters in equation (2.18) as a one-period-ahead earnings forecast model. Second, I approximate firm-level valuation parameters with estimates of their respective industry averages to estimate the implied 'other information' ϑ_t. Finally, I combine the valuation parameter estimates with forward earnings yield, book-to-price ratio and the implied 'other information' to construct the measure for one-period-ahead expected returns.

While other information ϑ_t is unobservable, it can be substituted with the linear pricing rule $\vartheta_t = P_t - (1 + \alpha_1)b_t - \alpha_2 x_t - \alpha_1 d_t$, after which equation (2.18) can be re-expressed as an earnings forecast model:

$$\begin{aligned}\mathbb{E}_t[x_{t+1}] = &\frac{ER_t - \phi}{1 + \alpha_1 + \alpha_2} P_t + \frac{\phi(\alpha_1 + \alpha_2)}{1 + \alpha_1 + \alpha_2} x_t \\ &+ \frac{\phi - \alpha_1 - 1}{1 + \alpha_1 + \alpha_2} b_t + \frac{\phi \alpha_1}{1 + \alpha_1 + \alpha_2} b_{t-1}\end{aligned} \quad (2.19)$$

Equation (2.19) captures the notion that prices lead earnings. That is, prices forecast earnings beyond information reflected in realized earnings and book values. If there exists a reasonable proxy for market earnings expectation $\mathbb{E}_t[x_{t+1}]$, equation (2.19) is an exactly identified model. In Hansen's (1982) terms, there are four 'instruments' ($E_t[x_{t+1}]$, x_t, b_t and b_{t-1}) and four 'parameters' (α_1, α_2, ϕ and ER_t). Surprisingly, ER_t is directly identified in the model. In fact, Ashton and Wang (2013) run annual cross-sectional estimations of this model to obtain aggregate cost of capital estimates in a constant expected return setting. However, at the firm level, estimating ER_t directly from this equation is not feasible. Cross-sectional estimation will produce the same expected return for all firms in a given year; similarly, time-series estimation for each firm will produce an estimate without time variation. As a practical compromise, we estimate cross-sectional average valuation parameters α_1, α_2 and ϕ for portfolios of homogeneous firms on a yearly basis and use these portfolio-level estimates to approximate firm-level parameter values.[25] Specifically, I estimate the following annual cross-sectional regression model for each industry partition:

$$\frac{\mathbb{E}_t[x_{t+1}^i]}{P_t^i} = \frac{\overline{ER}_t - \overline{\phi}}{1+\overline{\alpha}_1+\overline{\alpha}_2} + \frac{\overline{\phi}(\overline{\alpha}_1+\overline{\alpha}_2)}{\overline{1+\alpha_1+\overline{\alpha}_2}}\frac{x_t^i}{P_t^i} + \frac{\overline{\phi}-\overline{\alpha}_1-1}{1+\overline{\alpha}_1+\overline{\alpha}_2}\frac{b_t^i}{P_t^i} + \frac{\overline{\phi}\overline{\alpha}_1}{\overline{\alpha}_1+\overline{\alpha}_2}\frac{b_{t-1}^i}{P_t^i} + \varepsilon_t^i \tag{2.20}$$

where the over-lines and superscripts i are used to denote industry-level parameters and firm-level variables respectively. Note that while equation (2.19) holds exactly for each firm i and date t, equation (2.20) involves a firm-specific error term ε_t^i to the extent that industry average parameter values deviate from their firm-level counterparts. The scaling by price P_t ensures that the variables used for estimation are ergodic stationary to allow for statistical evaluations based on asymptotics (see, for instance, Hayashi 2000 , p97). While using any proxy for $\mathbb{E}_t[x_{t+1}]$ is bound to introduce measurement errors[26], estimates obtained from estimating equation (2.20) are still consistent because measurement errors do not affect the right-hand-side variables.

With a set of parameter estimates for $\overline{\alpha}_1$, $\overline{\alpha}_2$ and $\overline{\phi}$, I can then compute the firm-level implied 'other information' as:

[25]Implicitly, the estimation procedures used for most characteristics-based models such as Penman and Zhu (2017) and Lyle et al. (2013) are similar in spirit. That is, they assume the characteristic loadings are cross-sectional constants. Thus the cross-sectional variation derives from firm-specific characteristics.

[26]The measurement error comes from the fact that any proxy used may deviate from the true market expectation of the firm's next-period earnings.

$$\widehat{\vartheta}_t^i = P_t^i - (1+\overline{\alpha}_1)b_t^i - \overline{\alpha}_2 x_t^i - \overline{\alpha}_1 d_t^i \tag{2.21}$$

Finally, I construct the firm-level expected return by combining industry average parameter estimates and firm-level forward earnings yield, book-to-price ratio, and the implied 'other information':

$$\widehat{ER}_t^i = (1+\overline{\alpha}_1+\overline{\alpha}_2)\frac{\mathbb{E}_t[x_{t+1}^i]}{P_t^i} + (1+\overline{\alpha}_1)\frac{b_t^i}{P_t^i} + \overline{\phi}\frac{\widehat{\vartheta}_t^i}{P_t^i} \tag{2.22}$$

Note that only information available at date t is used to construct expected return ER_t, thus the look-ahead bias is avoided.

One notable advantage of this approach is that it requires only one-year-ahead earnings forecast, thus imposing fewer data requirements. By contrast, typical ICC models require earnings forecasts for two to four years out. When these forecasts are unavailable, prior studies typically drop the respective observations or impute the forecasts from other data. Such difficulties do not constrain the model described above. In addition, this model does not require earnings forecasts or earnings growth to be positive, whereas many ICC models based on earnings growth are inapplicable to loss firms and firms with negative expected growth.

Conceptually, the new model summarizes all return predictive information beyond the earnings yield and book-to-market ratio by the other information variable. This compares with the approach by Penman and Zhu (2017), who express the expected return as a linear combination of earnings yield, book-to-market ratio, and a 'growth component' that is instrumented by a vector of other accounting data. In this vein, it can be argued that the 'other information' variable utilized in the new model plays the same role as Penman and Zhu (2017) 'growth component', which is also consistent with the interpretation of other information as a summary measure of expected long-run growth due to uncertain future investment projects. Of course, whether using a single summary measure of long-run growth for capture expected return is valid is to be empirically examined.

2.4 Data and estimates

To estimate the new measure of one-year-ahead expected return, I obtain accounting data from Compustat Fundamentals Annual file. Stock return data are extracted from CRSP Monthly Stock File (MSF). Analyst forecasts, stock prices and numbers of shares outstanding are collected from IBES. I construct a base sample of all firms listed on the NYSE, Amex and NASDAQ identified at the intersection between Compustat, CRSP and IBES from 1985 to 2014. I exclude all non-equity issues such as ADRs (American depositary receipts) as indicated by CRSP share code (SHRCD). Table 2.1 outlines the sample construction procedure.

The estimation of expected returns require earnings (x_t), dividends (d_t) current and lagged book values of equity (b_t and b_{t-1}), and one-year-ahead analyst earnings forecasts ($FE_{t,t+1}$).[27] All variables are translated to per-share basis as per IBES number of shares outstanding unless otherwise indicated. Consistent with Penman and Zhu (2014), earnings are calculated as earnings before extraordinary items (Compustat item IB) plus special items (SPI), minus preferred dividends (DVP), with a tax allocation to special items at the statutory income tax rate for the year. Book value of equity is calculated as common equity (Compustat item CEQ), plus preferred treasury stock (TSTKP) and minus preferred dividends in arrears (DVPA). Dividends are measured as Compustat item DVT.[28] I exclude firm-year observations with negative book

[27] To the extent that analyst forecasts are biased upwards, the estimated expected return measure may be overstated (Easton and Monahan 2005).

[28] This measurement choice avoids share-based transactions.

Table 2.1: Construction of estimation sample

Data restrictions	Observations	Firms
Compustat data with non-missing x_t, d_t, $b_t > 0$ and $b_{t-1} > 0$	147,674	16,866
Less observations with newly acquired assets greater than 30% of total assets	(972)	(54)
Less observations with missing one-year-ahead analyst forecasts, share price and number of shares outstanding from IBES	(42,263)	(3,743)
Less observations without SIC codes from Compustat or not classified under Fama-French five-industry classification scheme	(15,902)	0
Less observations with b_t/P_t not in the range $(0.01, 100)$, x_t/P_t not in the range of $(-1, 1)$, and $P_t < 0.5$	(152)	(1,912)
Estimation sample	85,385	11,157

Notes: This table reports the effects sample selection restrictions on the estimation sample. The first column describes the data restrictions applied. The second and third columns reports their effects on the sample size in terms of total number of observations and the number of unique firms. Values in parentheses indicate reductions.

values or lagged book values and those heavily impacted by mergers and acquisitions activities as indicated if the total amount of acquired assets is estimated to be greater than 30% of the beginning balance of total assets.[29]

As a proxy for market expectation of one-year-ahead earnings ($\mathbb{E}_t[x_{t+1}]$), $FE_{t,t+1}$ is measured as the median analyst forecast (IBES item MEDEST) formed on the third Thursday of April following year t financial year end from the IBES Summary History file.[30] Stock prices (IBES item PRICE) and the numbers of shares outstanding (SHOUT) are based on IBES Pricing & Ancillary file, and are observed on the same date as $FE_{t,t+1}$.[31]

I accumulate one-year-ahead buy-and-hold stock returns R_{t+1} from May of year $t+1$ to April of year $t+2$. I follow Shumway's (1997) recommendation and apply -33% adjustment for delisting returns. The estimation is performed over five industries each year, using Fama and French (1997) five-industry classification scheme. SIC codes (Compustat item SICH) are used to perform the classifications.[32] Risk-free rates r_t^f are measured as the yield of 10-year treasury bonds, observed at the analyst forecast date. Following prior studies, I delete observations with book-to-price ratios (b_t/P_t) lower than 0.01 or higher than 100, earnings yields (x_t/P_t) lower than -1 or higher than 1, or stock prices lower than \$0.5 to mitigate effects of extreme values on estimations. After applying these restrictions, the estimation sample consists of $85,385$ firm-year observations with $11,157$ unique firms. This sample size

[29] I estimate the total amount of acquired assets as the sum of acquired inventory (ACQINVT), acquired property, plant and equipment (ACQPPE), acquired intangible assets (ACQINTAN), acquired goodwill (ACQGDWL), and acquired other assets (ACQAO). These data items are obtained from Compustat. Changing the cut off point 30% to 10% or 50% leaves almost no effects on any subsequent results.

[30] IBES typically compiles summary files for each firm on the third Thursday of each month.

[31] Because the items SHOUT and PRICE are not well populated before 1985 in the IBES version to which I have access, the sample period starts from 1985.

[32] I acknowledge that five-industry partition is not sufficient to achieve high levels of homogeneity. Unfortunately, given the requirement for sufficient data available for cross-sectional estimation, I cannot use more refined industry classification schemes. To mitigate related concerns, I replicate all analyses using no industry partition at all. The unreported results are qualitatively similar, though quantitatively weaker.

is considerably larger than those used in prior ICC studies that use analyst forecasts (e.g. Nekrasov and Ogneva 2011).

Table 2.2 reports the details of annual sample distributions across the five Fama-French industries. Over the 30-year sample period, the number of firms ranges from 2,211 in 1985 to 3,958 in 1997. Across the industries, I obtain a typical sample size of around 600 firms per year except for the Hlth industry, where the number of firms per year grew from only 120 in 1985 to 326 in 2014, peaking at 399 in 1997. Thus, the parameter estimates for the Hlth industry may be less precise than the estimates for other industries, especially in the early years of the sample period. Overall, Table 2.2 shows that the industry-year partitions produce reasonably well populated samples for estimation.

In the following sections, I will evaluate the empirical performance of the new measure of expected return with a battery of validation tests. These tests will require additional data including at least future realized one-period-ahead returns and a set of firm characteristics that have been shown to predict stock returns empirically. This reduces the size of the testing sample to 80,940 observations.

Table 2.3 Panel A provides sample descriptive statistics of the variables used in estimating equation (2.20) for constructing expected returns. The mean (median) of book-to-market ratio b_t/P_t is 0.62 (0.52), comparable to the sample means (medians) reported in prior studies (e.g. Nekrasov and Ogneva 2011). The forward earnings yield $FE_{t,t+1}/P_t$ is higher than the trailing earnings yield x_t/P_t at all reported percentiles of their distributions, consistent with analysts' tendency to issue optimistic forecasts.

Table 2.3 Panel B reports descriptive statistics of the testing sample. Note that the empirical distributions of b_t/P_t, x_t/P_t and $FE_{t,t+1}/P_t$ remain largely unchanged compared to the estimation sample, except for a notable rise in

Table 2.2: Sample distribution by year and industry classification

Year	Cnsmr	Manuf	HiTec	Hlth	Other	Total
1985	481	646	412	120	552	2,211
1986	512	638	438	132	558	2,278
1987	504	607	448	153	602	2,314
1988	517	600	451	165	615	2,348
1989	503	601	438	173	652	2,367
1990	506	593	410	181	627	2,317
1991	487	622	413	198	606	2,326
1992	554	638	428	264	633	2,517
1993	639	665	499	297	726	2,826
1994	706	715	589	318	979	3,307
1995	730	776	648	309	1,030	3,493
1996	719	803	781	333	1,090	3,726
1997	743	798	844	399	1,174	3,958
1998	710	759	829	389	1,158	3,845
1999	654	687	786	338	1,092	3,557
2000	563	607	863	304	992	3,329
2001	478	555	800	328	863	3,024
2002	457	531	697	317	852	2,854
2003	469	509	682	344	860	2,864
2004	481	517	703	353	877	2,931
2005	471	521	689	372	918	2,971
2006	483	540	646	369	920	2,958
2007	465	556	630	379	876	2,906
2008	441	552	603	347	819	2,762
2009	451	559	590	329	872	2,801
2010	438	555	560	315	781	2,649
2011	436	525	519	299	748	2,527
2012	409	510	523	297	749	2,488
2013	403	496	538	287	739	2,463
2014	384	486	528	326	744	2,468
Total	15,794	18,167	17,985	8,735	24,704	85,385

Notes: This table reports the distribution of sample observations across Fama and French's (1997) five industry portfolios over the sample period 1985–2014. Industry 'Cnsmr' includes consumer durables, non-durables, wholesale, retail, and some services (e.g. laundries, repair shops). Industry 'Manuf ' includes manufacturing, energy, and utilities. Industry 'HiTec' includes business equipment, telephone and television transmission. Industry 'Hlth' includes health care, medical equipment, and drugs. Industry definitions are obtained from Kenneth French's online data library `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

the lower tail of the distribution of x_t/P_t (with 1st percentile increased from -0.85 to -0.69), suggesting extreme loss makers fail to survive the additional data requirement. Average one-period-ahead buy-and-hold return $R_{t,t+1}$ is 12% with a large standard deviation of 48%.

Next, Panel B provides summary statistics of some commonly used risk proxies. Financial leverage Lev_t, calculated as total financial debt divided by the book value of equity, is highly right-skewed with its mean (0.635) far exceeding the median (0.215).[33] Firm size $Mcap_t$ is measured as the natural log of market capitalization on the analyst forecast date.[34] The log transformation of $Mcap_t$ smooths out the high skewness in firm size, with the mean and median both taking values just above 6. The mean CAPM beta $Beta_t$ is 1.14, slightly higher than the market average beta of 1, probably due to the fact that firms receiving analyst coverage exhibit stronger co-movement with the market (Lee and So 2017).[35] Momentum Mom_t is defined as the the buy-and-hold stock return over the 12-month period prior to the forecast date.

Prior studies also show that growth is related to risk and expected returns (Penman and Zhu 2014, 2017), so Panel B also summarizes some leading growth-related variables. Operating accrual Acc_t has a negative mean and median, consistent with prior findings that accruals tend to bear bad earnings news (Sloan 1996; Givoly and Hayn 2000). Net operating asset growth ΔNOA_t, percentage sales growth rate $Saleg_t$, investments in property, plant & equipment Inv_t and net external financing Exf_t all have positive mean and medians, indicating that firms typically experience positive growth.[36] Overall,

[33]Total financial debt is estimated by the sum of debt in current liabilities (Compustat item DLC) and debt in long-term liabilities (item DLT). Note that the extremely large 99th percentile is not due to a few extreme cases, as the the distribution of Lev_t between its 75th and 99th percentiles is indeed quite wide.

[34]Market capitalization is calculated as share price (PRICE) multiplied by number of shares outstanding (SHOUT) obtained from IBES.

[35]I estimate CAPM beta $Beta_t$ using at least 18 and up to 60 monthly stock returns prior to the earnings forecast date. Note that the market return used for estimating $Beta_t$ is CRSP value-weighted return, thus the mean beta in my sample is not necessarily one.

[36]Acc_t is measured as the sum of changes in receivables (Compustat item RECT), inventory (INVT) and other current assets (ACO), less depreciation and amortization charges (DP) and changes in other current liabilities (LCO). ΔNOA_t is calculated as the total

the summary statistics in Table 2.3 show that my sample is largely in line with prior studies.

The model parameters in equation (2.20) are obtained from cross-sectional estimations.[37] To estimate equation (2.20), one can reparameterize it into a linear regression and estimate its linear coefficients with ordinary least squares (OLS), and then reverse the reparameterization to uncover the underlying parameters $\overline{ER}_t$, $\overline{\phi}$, $\overline{\alpha}_1$ and $\overline{\alpha}_2$ (as in Ashton and Wang 2013). Standard errors of parameter estimates can be computed by applying the delta method. Slutsky's theorem ensures that consistent estimation of the linear coefficients will lead to consistent estimation of the model parameters (Hayashi 2000 , p92-93). However, to avoid reparameterization and complicated delta method computations, I use the numerically equivalent equal-weighting one-step generalized method of moments (GMM) to estimate (2.20), which estimates the nonlinear model parameters and provides their statistical properties directly.[38]

Table 2.4 presents annual GMM estimates of parameters in equation (2.20). The second, fourth and fifth columns report the time series of cross-sectional

changes in receivables (RECT), inventory (INVT), other current assets (ACO), property, plant and equipment (PPENB), intangible assets (INTAN) and other long-term assets (AO), less changes in payables (AP), and other current and long-term liabilities (LCO + LO). Inv_t is the sum of increments in the gross costs of property, plant and equipment and in inventory. Accr_t, ΔNOA_t and Invest_t are scaled by average assets of year t. Sgr_t is simply year-t change in sales (SALE) divided by sales of prior year. Exf_t equals the cash proceeds from long-term debt issues (item DLTIS) and equity issues (item SSTK) plus the net changes in current debt (item DLCCH) less cash payments for retiring long term debts (item DLTR), for equity share repurchases (item PRSKC) and for dividends (item CDVC).

[37] I replicate all subsequent analyses in this chapter by using 2-year and 5-year rolling-window estimations and lagged panel sample estimations in this step. The results are slightly weaker but quantitatively similar. This is because the use of rolling-window or lagged panel samples reduces the number of years available for cross-sectional analyses and reduces the variability of the valuation parameters and thus their power to capture time-varying conditional expectations.

[38] All subsequent analyses are replicated with OLS and the results are changed only due to negligible rounding errors. Using the standard two-step spectral density weighted GMM also produces almost identical results and is asymptotically more efficient (Hayashi 2000). However, I do not proceed with this two-step estimation because the size of a typical industry-year sub-sample is in the order of hundreds, meaning that the spectral density matrix estimates are likely to be unreliable (see, for example Ferson and Foerster 1994; Hansen et al. 1996; Cochrane 1996). Hence, one-step estimates are likely to be more robust in this case.

Table 2.3: Summary statistics

Variable	Mean	SD	P_1	P_{25}	Median	P_{75}	P_{99}
Panel A: Estimation sample N = 85,385							
b_t/P_t	0.620	0.490	0.071	0.318	0.520	0.781	2.357
x_t/P_t	0.002	0.267	−0.848	0.011	0.048	0.073	0.188
$FE_{t,t+1}/P_t$	0.051	0.098	−0.311	0.040	0.063	0.086	0.182
b_{t-1}/P_t	0.627	0.659	0.054	0.284	0.488	0.766	2.930
Panel B: Testing sample N = 80,940							
b_t/P_t	0.619	0.467	0.076	0.324	0.525	0.782	2.260
x_t/P_t	0.012	0.222	−0.689	0.016	0.050	0.075	0.187
$FE_{t,t+1}/P_t$	0.056	0.081	−0.247	0.043	0.065	0.087	0.182
$R_{t,t+1}$	0.121	0.480	−0.750	−0.179	0.074	0.339	1.788
Risk proxies							
Lev_t	0.612	1.680	0.000	0.032	0.215	0.635	6.134
$Mcap_t$	6.160	1.853	2.566	4.808	6.021	7.361	10.968
$Beta_t$	1.144	0.771	−0.219	0.637	1.042	1.502	3.702
Mom_t	0.187	0.672	−0.750	−0.158	0.096	0.381	2.480
Growth proxies							
Acc_t	−0.027	0.094	−0.275	−0.068	−0.030	0.009	0.259
ΔNOA_t	0.032	0.142	−0.306	−0.027	0.014	0.070	0.564
$Saleg_t$	0.117	0.334	−0.688	0.004	0.091	0.207	1.102
Inv_t	0.079	0.212	−0.224	0.001	0.038	0.106	0.763
Exf_t	0.055	0.167	−0.161	−0.006	0.008	0.060	0.795

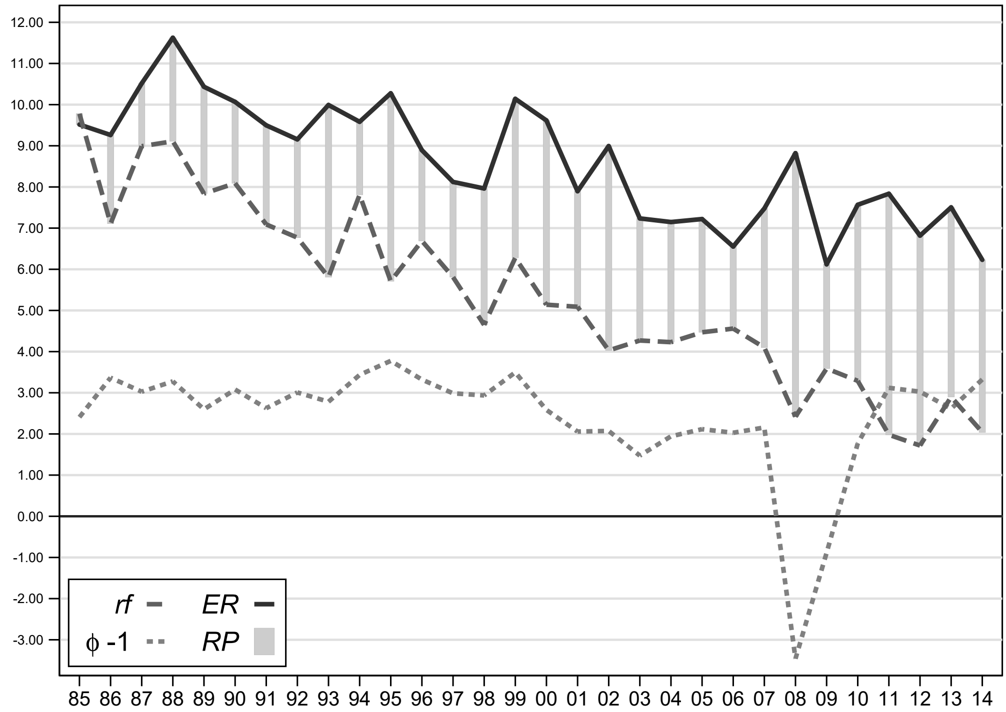
Notes: Panel A and Panel B report descriptive statistics for the estimation sample and testing sample respectively. Sample means, standard deviations, 1st, 25th, 50th, 75th and 99th percentiles are reported in columns 2-8 respectively. b_t/P_t is the book-to-price ratio. x_t/P_t and $FE_{t,t+1}/P_t$ are trailing and forward earnings yields respectively. b_{t-1}/P_t is the ratio of lagged book value per share over current stock price. Lev_t is financial leverage; $Mcap_t$ is the natural log of market capitalization; Acc_t is operating accruals; $Beta_t$ is CAPM beta; ΔNOA_t is net operating asset growth; $Saleg_t$ is realized (percentage) sales growth rate; Inv_t is firm investments in property, plant & equipment and inventory; Exf_t is total external financing; Mom_t is momentum (past 12-month buy-and-hold return); and $R_{t,t+1}$ is one-period-ahead realized return.

Table 2.4: Annual cross-sectional estimates of average valuation parameters

Year	ER	$t(ER)$	RP	r_t^f	$\phi - 1$	$t(\phi - 1)$	$\alpha_1 - 1$	$t(\alpha_1)$	α_2	$t(\alpha_2)$
1985	9.51	28.61	0.26	9.26	2.41	2.07	0.01	0.59	0.16	3.23
1986	9.26	21.35	2.15	7.11	3.37	5.36	0.02	0.97	0.21	3.40
1987	10.51	24.54	1.53	8.99	3.03	3.73	0.05	1.98	0.22	3.92
1988	11.62	37.97	2.52	9.11	3.28	3.85	0.03	1.54	0.40	4.84
1989	10.43	41.68	2.60	7.84	2.60	3.30	0.06	3.50	0.15	2.71
1990	10.06	37.31	1.35	8.08	3.08	2.99	0.03	2.27	0.22	4.48
1991	9.49	30.51	2.29	7.09	2.63	4.62	0.04	2.69	0.19	3.94
1992	9.15	24.83	2.39	6.77	3.01	4.16	0.03	1.52	0.18	3.03
1993	9.99	29.76	3.71	5.77	2.78	4.54	0.06	2.44	0.28	5.12
1994	9.58	35.28	2.11	7.81	3.44	6.00	0.01	0.67	0.28	4.84
1995	10.27	36.02	4.11	5.71	3.78	5.03	0.02	2.02	0.28	5.70
1996	8.89	29.14	2.44	6.30	3.32	7.28	0.04	2.31	0.18	3.77
1997	8.12	19.71	2.31	5.81	2.97	3.68	0.02	1.30	0.31	4.62
1998	7.96	16.61	3.31	4.65	2.94	4.07	0.03	0.69	0.25	4.34
1999	10.14	28.50	3.86	6.28	3.50	3.70	0.09	3.26	0.37	5.28
2000	9.61	12.49	4.03	5.24	2.58	2.61	0.00	-0.01	0.11	2.87
2001	7.89	15.58	2.76	5.09	2.06	2.05	0.06	1.06	0.18	4.22
2002	8.99	10.39	4.97	4.03	1.39	1.50	0.01	0.65	0.27	5.80
2003	7.23	13.94	2.97	4.27	1.47	2.43	0.02	0.46	0.34	5.13
2004	7.14	8.77	2.92	4.23	1.94	1.30	0.01	0.49	0.56	4.83
2005	7.22	14.35	3.04	4.47	2.12	1.56	0.04	1.80	0.53	5.02
2006	6.55	12.19	1.99	4.56	1.76	1.29	0.02	0.57	0.52	4.28
2007	7.47	9.37	3.38	4.10	2.16	1.44	0.01	0.41	0.30	4.39
2008	8.82	5.17	6.40	2.42	-3.46	-1.46	0.00	-0.01	0.15	3.75
2009	6.12	8.78	2.53	3.59	-1.66	-1.71	0.01	0.33	0.33	3.60
2010	7.46	16.94	4.18	3.29	1.77	1.56	-0.01	-0.34	0.43	4.97
2011	7.83	16.28	5.86	1.98	3.12	3.15	0.01	0.23	0.49	4.74
2012	6.81	9.44	5.10	1.72	3.03	1.84	0.04	1.45	0.33	3.87
2013	6.89	9.90	4.42	2.90	2.61	1.96	0.02	0.53	0.57	4.27
2014	7.61	7.70	5.08	2.21	3.32	2.04	0.15	2.70	0.70	4.61
Mean	8.57	19.50	2.96	5.24	2.63	2.99	0.03	1.18	0.27	4.28

Notes: This table reports cross-sectional average estimates from annual cross-sectional GMM estimations of equation (2.20). Column ER reports annual average expected return estimate $\overline{ER}_t$; column $t(ER)$ is the associated t-statistic of $\overline{ER}_t$. RP and r_t^f indicate expected risk premium and risk-free rate respectively, where RP is the difference between ER and r_t^f and r_t^f is the yield of 10-year treasury bond. Columns $\phi - 1$ and $t(\phi)$ report estimates and t-statistics of $\overline{\phi} - 1$. Columns α_1 and α_2 ($t(\alpha_1)$ and $t(\alpha_2)$) report estimates (t statistics) of $\overline{\alpha}_1$ and $\overline{\alpha}_2$ respectively Values in columns ER, RP, r_t^f and $\phi - 1$ are reported in percentage scale, and values in remaining columns are reported in raw scales.

Figure 2.1: Time-series plot of expected returns and implied other information growth



average expected returns $\overline{ER}_t$, expected risk premia $\overline{ERP}_t$ and risk-free rates r_t^f. Figure 2.1 plots these data over time. The time-series average expected return is 8.57% and the average risk premium is just under 3%, which is quite similar to the those reported in Claus and Thomas (2001), Gebhardt et al. (2001), Easton et al. (2002), Nekrasov and Ogneva (2011) and Ashton and Wang (2013). All estimates of expected returns are highly significant with annual t-statistics averaging at 19.50. Expected return $\overline{ER}_t$ is generally declining over the sample period from around 10% to 7-8%, mainly due to the apparent decline in the 10-year treasury yield r_t^f, leaving the risk premium mostly stationary. Notably, the risk premium $\overline{ERP}_t$ increased after the 1987 black Monday, 1990 recession, 2001 'tech bubble' burst and the 2007-2008 sub-prime debt crisis. This seems to be consistent with the notion that risk premiums tend to be high when the overall market and economy suffer.

Table 2.4 and Figure 2.1 also track the estimate $\overline{\phi} - 1$ over time. I find that all estimates of $\overline{\phi} - 1$ are positive and around 3% except for the years 2008 and 2009, when it sharply dropped to -3.5% in the middle of the most recent global financial crisis (GFC).[39] Ashton and Wang (2013) interpret the quantity $\overline{\phi} - 1$ as the growth rate in 'other information', which is likely to capture the effect of macroeconomic growth on asset prices. Indeed, this growth rate averages around 2.6%, which is in the order of typical US GDP growth over the sample period. It bottomed in 2008 but rebounded to around 4% after the GFC, signaling strong signs of economic recovery. These observations seem to validate the Ashton and Wang (2013) interpretation.[40]

The last four columns in Table 2.4 provides point estimates and t-statistics of the linear pricing parameters. Most estimates of $\overline{\alpha}_1$ are very close to one, with $\overline{\alpha}_1 - 1$ mostly positive but insignificantly different from zero in all but nine years in the sample. These estimates are much higher than the estimates of Dechow et al. (1999), who suggest that the market pricing of book value is too low.[41] All estimates of $\overline{\alpha}_2$ are significantly positive, consistent with earnings positively contributing to market price after controlling for book values, dividends and other information.

Overall, the behavior of average model estimates reflects the effects of significant economic events and is consistent with prevailing economic intuitions. In the next two sections, I perform external validation tests to evaluate the quality of the new expected return measure at the portfolio and firm level.

[39]Note that this finding shows that other information in stock prices may not converge to zero in the long run. However, it can been seen that $\overline{\phi} < R_t^f$ except for 3 years after the GFC, consistent with the co-integration requirement in Assumption 4.

[40]It is also interesting to note that the statistical significance of $\overline{\phi} - 1$ has declined over the years, for which a possible explanation is the increasing heterogeneity between firms in the industry classifications over time.This may have caused the precision of the estimates to decline.

[41]Of course, the estimates of $\overline{\alpha}_1$ are not of direct interest to my study. In addition, Dechow et al. (1999) estimates are obtained from a different methodology for a different research purpose, so a rigorous comparison is not made.

2.5 Portfolio returns and associations with firm characteristics

My first validation test is based on portfolio-level associations of the new expected return measure with future realized returns and commonly used risk and growth proxies.

An important question in evaluating the usefulness of an expected return measure is whether an investor can expect to earn economically meaningful gains if she forms portfolios based on the measure. Thus, it is important to test whether a long-short strategy based on the expected return measure is associated with sizable out-of-sample gains. This approach is also useful in mitigating the measurement errors in the expected return measure as firm-level measurement errors are 'smoothed out' at the portfolio level (Easton and Monahan 2005). Table 2.5 reports time-series averages of future realized returns on cross-sectional expected-return-sorted decile portfolios over various investment horizons. Over a one-year horizon, the new expected return measure ER_t monotonically sorts realized returns except for the highest (10th) decile. An investor who follows a zero-cost strategy going long on the 10th and short on the 1st decile portfolios is expected to earn a statistically significant and economically large 9.87% (t-statistic 11.61) return over the next year. Thus, the new measure significantly predicts one-period-ahead realized return in the cross-section.

The ability of ER_t to rank future realized returns remains highly significant up to 10 years out, and the statistical significance of the long-short strategy is not seriously impaired up to five years out from the date of portfolio formation. These results shows that while ER_t is designed to measure one-period-ahead expected returns, it is persistent enough to forecast economically large cross-sectional spreads in realized return up to at least 10 years out-of-sample.

Table 2.5: Future realized returns on cross-sectional expected-return-sorted portfolios

Deciles	ER_t	$R_{t,t+1}$	$R_{t,t+2}$	$R_{t,t+3}$	$R_{t,t+4}$	$R_{t,t+5}$	$R_{t,t+10}$
1 (low)	.0153	.0517	.2096	.3593	.4860	.6534	2.190
2	.0508	.1115	.2264	.4096	.5257	.7015	2.276
3	.0653	.1121	.2333	.3989	.5417	.7421	2.165
4	.0758	.1135	.2534	.4208	.5941	.7866	2.328
5	.0846	.1283	.2762	.4424	.6370	.8161	2.203
6	.0929	.1425	.2905	.4493	.6257	.8422	2.170
7	.1021	.1459	.3003	.4746	.6904	.9381	2.372
8	.1144	.1539	.3025	.4867	.6971	.9138	2.391
9	.1356	.1566	.3332	.5473	.8168	1.116	3.170
10 (high)	.2059	.1504	.3429	.5799	.8723	1.144	3.028
High-low return		**.0986**	**.1333**	**.2205**	**.3863**	**.4905**	**.8380**
t-statistics		11.61	8.04	8.16	10.86	10.06	3.58

Notes: This table reports time-series average future realized returns on cross-sectional expected-return-sorted decile portfolios over 1-, 2-, 3-, 4-, 5- and 10-year horizons. All portfolios are equal-weighted portfolios. $R_{t,t+j}, j = 1, 2, 3, 4, 5, 10$ is the realized return from date t to date $t + j$. The second last row reports returns to buying the 10th and selling the 1st decile portfolios over the respective horizons, and the last row reports their respective t-statistics.

I next examine the relation between the new expected return measure and a range of firm characteristics Botosan and Plumlee (2005) and Botosan et al. (2011) suggest that a reasonable expected return measure should be well associated with firm characteristics that serve as 'risk proxies'. While this argument is intuitive, the identity of 'risk proxies' is controversial, which leads Easton and Monahan (2016) to caution against this approach to assessing the validity of expected return measures. Table 2.6 examines the relation between expected returns and firm characteristics on the portfolio basis. The first five reported risk proxies include book-to-market ratio (b_t/P_t), firm size ($Mcap_t$), leverage (Lev_t), CAPM beta ($Beta_t$) and 'momentum' (Mom_t, i.e. buy-and-hold return over the past 12 months).[42] The results show that firms with

[42]While these variables are commonly used in empirical asset pricing applications, their identity as risk proxies is nonetheless far from robust. b_t/P_t has been shown to correlate with analyst forecast errors (Piotroski and So 2012); $Mcap_t$ has been shown to have lost its power to predict returns (Van Dijk 2011); Lev_t has been shown to negatively predict stock returns in several studies (e.g. Chava and Purnanandam 2010); $Beta_t$ is notorious for its poor association with stock returns despite its deep theoretical appeal (e.g. Frazzini and Pedersen 2014); and Mom_t predicts future stock return reversals, inconsistent with any risk-based explanation (Jegadeesh and Titman 1993).

higher expected returns tend to have higher book-to-market ratios, smaller market capitalizations, and higher financial leverage, consistent with their univariate associations of these variables with realized returns, although the ranking is not monotonic. Momentum appears to be decreasing in expected return from the 2nd to the 9th deciles, roughly consistent with the reversal patterns of stock returns over 12-month or longer horizons (Jegadeesh and Titman 1993). CAPM beta, however, appears to exhibit a U-shaped relation with expected return and the 1st decile portfolio has higher betas than the 10th portfolio, which is inconsistent with its theoretical relation with expected returns.

Table 2.6: Firm characteristics for cross-sectional expected-return-sorted portfolios

Deciles	b_t/P_t	$Mcap_t$	Lev_t	$Beta_t$	Mom_t	ΔNOA_t	Acc_t	Inv_t	Exf_t
1	.757	5.31	.629	1.52	.080	.0207	-.0491	.0777	.142
2	.577	6.09	.407	1.29	.262	.0412	-.0287	.0975	.0726
3	.534	6.37	.374	1.17	.241	.0388	-.0289	.0952	.056
4	.544	6.44	.427	1.08	.245	.0323	-.0292	.0841	.0416
5	.566	6.43	.470	1.03	.219	.0326	-.0242	.0787	.0365
6	.592	6.41	.559	.997	.218	.0285	-.0226	.0706	.0333
7	.623	6.22	.631	1.01	.198	.0292	-.0192	.0714	.0343
8	.660	6.15	.767	1.05	.195	.0343	-.0173	.0772	.0399
9	.705	5.89	.934	1.13	.160	.0356	-.0145	.0842	.0524
10	.732	5.55	1.11	1.20	.079	.0294	-.023	.0856	.0797

Notes: This table reports time-series average firm characteristics of cross-sectional expected-return-sorted decile portfolios. All portfolio values are equal-weighted. b_t/P_t is the book-to-market ratio, $Mcap_t$ is the natural logarithm of the market capitalization, Lev_t is financial leverage, $Beta_t$ is CAPM beta, Mom_t is momentum, NOA_t is growth in net operating assets, Acc_t is accruals, Inv_t is investments, and Exf_t is net external financing. Detailed definitions are given in the text.

Table 2.6 also reports the means of four 'growth proxies' across expected return deciles. These variables have been shown to negatively predict future returns (Lakonishok et al. 1994; Sloan 1996; Fairfield et al. 2003; Zhang 2007; Penman and Zhu 2014, 2017). The patterns again appear to be mixed and puzzling. While net operating asset growth ΔNOA_t is decreasing in expected returns from the 2nd to 10th deciles, accruals Acc_t, investments Inv_t and external financing Exf_t are not associated with expected returns in a manner consistent with their empirical predictive relation with realized returns.

One potential explanation for the mixed findings reported in Table 2.6 is the lack of power of univariate tests. Thus, I perform multivariate analysis by estimating the cross-sectional relationship between expected returns and the firm characteristics. I control for forward earnings yield in these regressions. The results are reported in Table 2.7. The most striking finding in Table 2.7 is that ER_t is significantly negatively associated with b_t/P_t, which is potentially surprising to the reader. However, Ohlson (2005b) analytically shows that, after controlling for forward earnings yield, the expected return is negatively related to book-to-market ratio in the presence of growth. The theoretical construction of ER_t also makes the source of negative relation clear: implied other information ϑ_t is negatively related to book-to-market ratio because low valuation (i.e. high b_t/P_t) is associated with lower future earnings expectations. Turning to the other 'risk proxies', note that $Beta_t$ receives positive and marginally significant coefficients, $Mcap_t$ receives highly significant and negative coefficients, Lev_t loads significantly positively on ER_t, and Mom_t continues to imply a return reversal in expected return.

Columns (1) to (3) in Table 2.7 include only one of the 'growth proxies' to account for potential high correlations between these variables by construction.[43] Now all these variables start to receive negative coefficients, consistent with their empirical relation to realized returns. ΔNOA_t is highly significant with t-statistics of -7.38 and Inv_t is only significant at the 10% level, but Acc_t marginally fails to meet any conventional significance level. In the last column, when all the 'growth proxies' are included, only ΔNOA_t continues to be significant, and the sign of the coefficient on Acc_t turns negative yet insignificant.

Overall, the results in Table 2.7 shows that the associations of ER_t with firm characteristics are mostly consistent with prior expectations. However, caution must be applied when interpreting these findings because there is little

[43]Refer to variable definitions provided in Section 2.4.

Table 2.7: Fama-Macbeth regressions of expected returns on firm characteristics

	Dependent variable: ER_t			
	(1)	(2)	(3)	(4)
$FE_{t,t+1}/P_t$	0.487***	0.488***	0.486***	0.488***
	(11.18)	(11.05)	(11.14)	(11.11)
b_t/P_t	-0.0216***	-0.0212***	-0.0214***	-0.0219***
	(-7.60)	(-7.48)	(-7.49)	(-7.62)
$Beta_t$	0.00151	0.00148*	0.00143	0.00165*
	(2.03)	(2.05)	(1.98)	(2.29)
$Mcap_t$	-0.00293***	-0.00294***	-0.00292***	-0.00295***
	(-8.83)	(-8.81)	(-8.61)	(-8.70)
Lev_t	0.00229***	0.00226***	0.00225***	0.00224***
	(9.98)	(10.16)	(9.72)	(10.20)
Mom_t	-0.0108**	-0.0107**	-0.0109**	-0.0108**
	(-3.57)	(-3.51)	(-3.56)	(-3.57)
ΔNOA_t	-0.0209***			-0.0228***
	(-7.38)			(-4.87)
Acc_t		-0.00875		0.0116
		(-1.93)		(1.65)
Inv_t			-0.00635*	-0.00174
			(-2.63)	(-0.74)
constant	0.0865***	0.0856***	0.0866***	0.0872***
	(18.59)	(18.34)	(18.32)	(18.25)
R^2	0.197	0.195	0.195	0.197

Notes: This table reports time-series average coefficients of annual cross-sectional regressions of ER_t on firm characteristics. t-statistics are reported in parentheses below the coefficient estimates. The t-statistics are calculated using Fama and MacBeth (1973) procedure. R^2 is the time-series mean R-squared across annual cross-sectional regressions. $FE_{t,t+1}/P_t$ is the forward earnings yield, b_t/P_t is the book-to-market ratio, $Mcap_t$ is the natural logarithm of the market capitalization, Lev_t is financial leverage, $Beta_t$ is CAPM beta, Mom_t is momentum, NOA_t is growth in net operating assets, Acc_t is accruals, and Inv_t is investments. Detailed definitions are given in the text.

a priori guidance on how expected returns *should* be associated with these firm characteristics.

2.6 Regression-based validation tests

To further validate the predictive ability of ER_t for future realized returns, I perform several regression-based validation tests. The validation methodology is based on a tautological decomposition of realized stock returns (Campbell and Shiller 1988; Campbell 1991; Vuolteenaho 2002). To start with, the realized return $R_{t,t+1}$ can be decomposed into 'true' expected return ER_t^* plus 'news' ε_{t+1}^*, such that ER_t^* is the conditional expectation and ε_{t+1}^* is of zero mean and not *ex ante* forecastable:

$$R_{t,t+1} = ER_t^* + \varepsilon_{t+1}^*$$

This implies that the true expected return ER_t^* predicts realized return one-to-one. Of course, ER_t^* is latent and any empirical measure $\hat{\mu}_t$ is bound to involve measurement errors. Consider the following regression model

$$R_{t,t+1} = \delta_0 + \delta_1 \hat{\mu}_t + \varepsilon_{t+1} \tag{2.23}$$

An unbiased expected return measure should measure $ER^*{}_t$ with a zero-mean measurement error, thus $\mathbb{E}[R_{t,t+1}|\hat{\mu}_t] = \hat{\mu}_t$. This implies that the slope coefficient δ_1 should be close to one and the intercept δ_0 should be close to zero.

However, as is discussed in Lee et al. (2015), in most research settings, the focus is on the *relative* levels of expected returns, and the bias in the measurement error is often neutralized and thus irrelevant for almost all applications.[44] Thus, the central issue regarding assessing the quality of an expected return measure is how closely the *variation* in $\hat{\mu}_t$ 'tracks' the *variation* in μ_t. In this spirit, a good measure $\hat{\mu}_t$ should produce δ_1 significantly positive and close to one, and the intercept is allowed to differ from zero to absorb the measurement bias. Of course, due to the attenuation effect of measurement errors in the independent variable, the coefficient is expected to be smaller than one.

While this approach is theoretically sound, Easton and Monahan (2005) and Easton and Monahan (2016) point out that the news component ε^*_{t+1} is likely to have a non-zero mean in the finite sample and be correlated with expected returns in the post-war US data.[45] Thus, they develop a method that explicitly controls for proxies of the news component ε^*_{t+1}. Specifically, Easton and Monahan (2005) specify the following regression model based on the Vuolteenaho (2002) return decomposition framework:

$$r_{t,t+1} = \delta'_0 + \delta'_1 er_t + \delta'_2 cfn_{t+1} - \delta'_3 drn_{t+1} + \varepsilon'_{t+1} \tag{2.24}$$

where $er_t = log(1 + \hat{\mu}_t)$, $r_{t,t+1}$ is the log of one plus one-period-ahead realized return, and cfn_{t+1} and drn_{t+1} are contemporaneously measured cash flow news and discount rate news respectively. An expected return measure that is perfectly correlated with the 'true' expected return should lead to ap-

[44] Lee et al. (2015) surveyed more than 80 papers published in top accounting and finance journals that use some measures of expected returns. Only three of these papers require unbiasedness of the expected return measures, while the others are concerned with cross-sectional or time-series variations in expected returns. Of course, in settings such as capital budgeting and corporate valuation, the unbiasedness is an important attribute of a good expected measure.

[45] Easton and Monahan (2016) attribute this to the extraordinary success of the US economy and capital market development in the post-war period.

proximately $\delta_1' = \delta_2' = \delta_3' = 1$.[46] In this study, I measure cash flow news as

$$
\begin{aligned}
cfn_{t+1} &= \frac{roe_{t+1} - froe_{t,t+1}}{1 - 0.96\kappa_c} \\
&= \frac{log(1 + x_{t+1}/b_t) - log(1 + FE_{t,t+1}/b_t)}{1 - 0.96\kappa_c}
\end{aligned}
$$

where κ_c is the expected persistence of roe_{t+1} estimated from a two-year cross-sectional hold-out sample for each industry.[47] The second equality defines roe_{t+1} and $froe_{t,t+1}$. The number 0.96 is approximately one minus historical average dividend yield.[48] This measure of cfn_{t+1} is consistent with Easton and Monahan (2005) except that it only requires one-year-ahead earnings forecasts to avoid further data loss.[49]

Discount rate news is measured as the following:

$$
\begin{aligned}
drn_{t+1} &= \frac{er_{t+1} - \kappa_r er_t - \bar{r}}{1 - 0.96\kappa_r} \\
&= \frac{log(1 + ER_{t+1}) - \kappa_r log(1 + ER_t) - \bar{r}}{1 - 0.96\kappa_r}
\end{aligned}
$$

where $\bar{r}$ and κ_r are the constant and persistence parameters of the expected return process. Because the new measure of expected return is time-varying, this

[46] Note that this relation is not exact because the Vuolteenaho (2002) return decomposition is based on first-order Taylor approximation.

[47] All estimates of κ_c are significantly below 1, thus rejecting unit roots.

[48] Vuolteenaho (2002) estimates this value to be 0.97, Easton and Monahan (2005) estimate this value to range from 0.95 to 0.985. Empirically, as long as it is slightly smaller than one, the exact value chosen has no impact on almost all applications, so I do not estimate it. Rather, I replicate all subsequent analyses after replacing 0.96 with 0.95, 0.97 and 0.98, and the results are unaffected.

[49] Da and Warachka (2009) propose a measure of cash flow news based on long-horizon analyst forecast revisions. However, this approach is not pursued because this would either impose strict data availability requirements or require some imputation of missing forecasts based on questionable analysts' long-term growth forecasts. My measurement choice reflects my intention to evaluate the expected return estimates for the largest sample possible for which some reliable data inputs are available.

measure of drn_{t+1} differs considerably from that used in Easton and Monahan (2005), which applies only to models assuming constancy of expected returns. Implicitly in this measurement, I assume expected return follows a first-order affine process, which is a common assumption in expected return models that admit time-varying expected returns.

Pooled regressions

I first run pooled regression tests to evaluate the quality of the new expected return measure ER_t. I consider four model specifications for the regression tests. In model (1), I run the univariate test as in equation (2.23) after log-transformations of realized and expected returns. In model (2), I estimate equation (2.24) by augmenting the model (1) with estimated cfn_{t+1} and drn_{t+1}. Model (3) regresses log realized returns on a vector of firm characteristics examined in Tables 2.6 and 2.7, and model (4) includes all variables in estimation to test if the explanatory power of er_t for realized returns is incremental to these variables.

Table 2.8 reports the regression coefficients, their two-way robust t-statistics and adjusted R^2s. Note that the requirement for non-missing values for cfn_{t+1} and drn_{t+1} further restricts the testing sample to 62,882 firm-year observations. In the univariate specification, model (1) produces a slope coefficient of 0.894, which is highly significant (t-statistic 20.55) and numerically close to the theoretical value of one. In comparison, leading ICC measures typically receive coefficients between 0.2 and 0.5 (see, for example, Table 3 of Lee et al. 2015). In addition, the regression intercept is statistically insignificant, suggesting the bias in er_t is small. Nonetheless, the t-test rejects the null that the slope coefficient is one at 95% level (p-value 0.0152).

Model (2) reports a 1.131 coefficient on er_t, 0.854 on cfn_{t+1} and -0.922 on drn_{t+1} —all numerically close to one. Notably, the adjusted R^2 is considerably

Table 2.8: Pooled regression test of the association of expected returns and realized returns

Models	(1)	(2)	(3)	(4)
Dependent variable: $r_{t,t+1}$ (test sample N=62,882)				
er_t	0.894***	1.131***		1.027***
	(20.55)	(26.56)		(24.34)
cfn_{t+1}		0.854***		0.854***
		(46.37)		(45.59)
drn_{t+1}		-0.922***		-0.882***
		(-28.73)		(-27.53)
b_t/P_t			0.103***	0.0846***
			(20.28)	(17.42)
$Mcap_t$			0.00512***	-0.00654***
			(5.67)	(-7.64)
Lev_t			0.00608***	0.00565***
			(4.34)	(4.27)
$Beta_t$			-0.0308***	-0.0131***
			(-12.20)	(-5.44)
ΔNOA_t			-0.170***	-0.101***
			(-9.56)	(-5.95)
Acc_t			-0.0238	-0.0773***
			(-0.96)	(-3.34)
Inv_t			-0.0462***	-0.0382***
			(-3.80)	(-3.35)
Constant	0.00265	0.0173***	0.0280**	0.0365***
	(0.65)	(4.33)	(3.25)	(4.06)
adj. R^2	0.032	0.145	0.050	0.164

Notes: This table reports coefficients of pooled regressions of the log of one-year-ahead realized return on the log of expected return er_t, cash flow news cfn_{t+1}, expected return news drn_{t+1}, and other firm characteristics. b_t/P_t is the book-to-market ratio, $Mcap_t$ is the natural logarithm of the market capitalization, Lev_t is financial leverage, $Beta_t$ is CAPM beta, Mom_t is momentum, NOA_t is growth in net operating assets, Acc_t is accruals, and Inv_t is investments. Detailed definitions are given in the text. Model (1) to (4) indicate four different regression specifications.

improved to 14.5% compared to that of model (1) (3.2%). It appears, however, that adding cash flow news and discount rate news proxies has introduced additional measurement bias, giving rise to a significant intercept. An F-test rejects the joint hypothesis that coefficients on er_t, 0.854 and cfn_{t+1} are equal to one and the coefficient on drn_{t+1} is -1.

Model (3) estimates show that the set of firm characteristics explain as much as 5% of total variation in one-period-ahead realized returns. The results for model (4) show that the predictive ability of er_t for $r_{t,t+1}$ is robust to controlling for cash flow news, discount rate news and firm characteristics simultaneously.

Cross-sectional regressions

While the pooled regression results seem to support that the new measure of expected return has sensible predictive power for one-period-ahead realized returns, most applications of expected return measures concern whether investors can improve their cross-sectional portfolio strategies using these measures. Hence, I next evaluate the performance of the measure in the cross-section.

Table 2.9 presents the cross-sectional regression results based on Fama and MacBeth (1973) coefficient aggregation method. The second column (labeled 'univariate') shows that in a univariate regression, the expected return measure er_t claims a positive coefficient of 0.570, which is significantly positive (t-statistic 4.05) yet statistically different from one at 5% level (p-value 0.0047). Nonetheless, compared to other leading measures of expected returns, it appears that er_t outperforms leading ICC mesaures.[50]

[50] Guay et al. (2011) report that most ICC measures receive coefficients between -0.33 and 0.43 in univariate cross-sectional regressions, and these coefficients are not statistically distinguishable from zero at conventional levels.

Table 2.9: Cross-sectional regression test of the association of expected returns and realized returns

	Univariate	EM	Extended EM
Dependent variable: $r_{t,t+1}$ (test sample N=62,882, T=30)			
er_t	0.570***	0.823***	0.736***
	(4.05)	(5.89)	(6.44)
cfn_{t+1}		0.845***	0.830***
		(18.36)	(21.47)
drn_{t+1}		-0.626***	-0.591***
		(-6.13)	(-5.59)
b_t/P_t			0.0315*
			(2.74)
$Mcap_t$			-0.00373
			(-1.16)
Lev_t			0.00388
			(1.45)
$Beta_t$			-0.0105
			(-0.76)
ΔNOA_t			-0.0245
			(-0.96)
Acc_t			-0.109*
			(-2.64)
Inv_t			-0.0522
			(-2.02)
Constant	0.00924	0.0236	0.0474
	(0.28)	(0.72)	(1.37)
Average R^2	0.009	0.121	0.137

Notes: This table reports time-series average coefficients of annual cross-sectional regressions of the log of one-year-ahead realized returns $r_{t,t+1}$ on the log of expected return er_t, cash flow news cfn_{t+1}, discount rate news drn_{t+1}, and other firm characteristics. t-statistics are reported in parentheses below the coefficient estimates. The t-statistics are calculated using Fama and MacBeth (1973) procedure. R^2 is the time-series mean R-squared across annual cross-sectional regressions. b_t/P_t is the book-to-market ratio, $Mcap_t$ is the natural logarithm of the market capitalization, Lev_t is financial leverage, $Beta_t$ is CAPM beta, Mom_t is momentum, NOA_t is growth in net operating assets, Acc_t is accruals, and Inv_t is investments. Detailed definitions are given in the text.

In the third column labeled 'EM', I report estimates based on Easton and Monahan (2005) regression, which form the main result of this section. EM regression has proved a hard test in the literature, as most leading ICC measures are found to be negatively associated with realized returns after controlling for cfn_{t+1} and drn_{t+1} (Easton and Monahan 2005; Nekrasov and Ogneva 2011).[51] The results suggest that the new measure er_t significantly outperforms leading ICC measures. The coefficient on er_t is 0.823, which is highly significant (t-statistic 5.89) and statistically indistinguishable from one (p-value 0.216). The intercept also remains statistically insignificant. In addition, the coefficients on cash flow news and especially discount rate news proxies are also more reasonable than those reported in prior studies. The coefficient on cfn_{t+1} is 0.823, which is suggestively close to one, although it is statistically different from one (p-value 0.002) due to its small standard error. The coefficient on drn_{t+1} amounts to -0.626, which is much closer to -1 than discount rate proxies computed from existing ICC measures. This reflects a much stronger negative association between discount rate news and contemporaneous realized returns. In comparison, even discount rate news proxies based on the best-performing ICC measures receive coefficients lower than 0.20, suggesting that stock returns appear insensitive to discount rate changes. (Easton and Monahan 2005; Nekrasov and Ogneva 2011; Mohanram and Gode 2013).

The last column of Table 2.9 reports estimates from an 'extended' version of EM regression. Specifically, I regress $r_{t,t+1}$ on er_t, cfn_{t+1}, drn_{t+1} and a vector of firm characteristics that have been shown to predict stock returns in the cross-section. The coefficient estimates on er_t, cfn_{t+1} and drn_{t+1} are quantitatively similar to those in EM regression, although the coefficient on er_t becomes statistically distinguishable from one at the 99% level (p-value 0.028) due to its correlation with firm characteristics. Importantly, it seems that only

[51] To my knowledge, no existing ICC measure based on analyst forecasts receives a coefficient close to one and significantly above zero in EM regressions. The measure proposed by Nekrasov and Ogneva (2011) marginally meets this criterion only after it is adjusted for predictable analyst forecast errors.

b_t/P_t and Acc_t remain marginally significant in explaining the cross-section of realized returns, once expected returns and news proxies are controlled for. In other words, the return predictive role of most of these characteristics is 'driven out'. These results suggest the new measure of expected return exhibits strong association with one-period-ahead realized returns in the cross-section.

2.7 Summary

In this chapter, I develop and evaluate a new method for constructing a measure of one-period-ahead expected returns from firm fundamentals. The measure is forward looking and admits time-varying expected risk premiums through time-varying volatility in the firm fundamentals. It also avoids making arbitrary assumptions about firms' terminal payoff growth rates and dividend policies. The expected return estimates show a strong association with future realized returns and consistent associations with a range of return predictive variables.

Chapter 3

Alpha versus Beta: Firm fundamentals in the cross-section of expected returns

3.1 Introduction

The cross-sectional variation in expected returns is predictable by a wide array of firm fundamentals (Daniel and Titman 1997; Green et al. 2013; Lewellen et al. 2015; Green et al. 2016). The return predictive ability of many of these firm fundamentals is not subsumed by leading covariance-based asset pricing models (Fama and French 1996, 2008; Hou et al. 2015; Fama and French 2016) and is highly reliable out-of-sample (Lewellen et al. 2015).

These findings have led accounting researchers to devise characteristics-based models for estimating expected returns or costs of equity capital (Lyle et al. 2013; Lewellen et al. 2015; Lyle and Wang 2015; Penman and Zhu 2017). Penman and Zhu (2017), for example, estimate expected returns from historical relationship between stock returns and firm fundamentals including earning yield, book-to-market ratio, sales growth rate, accruals, investment, net operating asset growth, external financing and net share issue. They find that their expected return estimates meaningfully predicts future realized returns, while estimates from conventional covariance-based asset pricing models and implied cost of capital models fail to do so. However, the question remains regarding whether the relative 'success' of characteristics-based models is due to their ability to measure risk or their ability to capture mispricing.[52]

As an indoctrinated principle in asset pricing, rational investors demand compensation only for bearing systematic covariance risks – exposures to market-wide risk factors whose volatility cannot be diversified away. Stocks earn higher expected returns if and only if they exhibit greater (smaller) exposures (i.e. betas) to risk factors that have positive (negative) risk premiums.[53] Once the firm-specific betas are controlled for, characteristics (including firm fundamentals) have no incremental predictive power for stock returns (i.e. alphas).[54] However, Daniel and Titman (1997) and Lin and Zhang (2013) find that firm fundamentals dominate betas in statistical horse races for forecasting stock returns. Daniel and Titman (1997) interpret this finding as evidence of pervasive mispricing in the market, and the predictive power of firm fundamentals for stock returns is due to their contributions to alphas. In contrast, Lin and Zhang (2013) contend that characteristics-based models are conceptually equivalent to covariance-based models for measuring risk and expected returns and that the poor performance of covariance risk measures for capturing cross-sectional stock returns is due to the ambiguous identity of true risk factors and imprecise measurement of risk exposures.[55]

[52]Penman and Zhu (2017) attribute the predictive ability of their model for future returns to better risk measurement, but they acknowledge that they cannot formalize the argument.

[53]Firm-specific factor betas are covariances 'standardized' by variances of respective market-wide risk factors. Hence, I use the terms 'betas', 'covariance risks' and 'risk exposures' interchangeably in this chapter.

[54]In asset pricing tests, significant alphas are typically regarded as evidence of mispricing.

[55]Fama and French (1992) also informally argue that book-to-market and firm size are proxies for firm exposure to common risk factors.

The latter point is key to distinguishing firm fundamentals that constitute risk measurement from those that capture mispricing. Specifically, a firm fundamental variable represents risk measurement if and only if it consistently forecasts betas. That is, characteristics that positively (negatively) forecast stock returns must also positively (negatively) forecast the stock's covariances with common risk factors that are associated with positive (negative) risk premiums. This chapter explicitly tests this criterion for a wide array of firm fundamentals. In designing the tests, I attempt to circumvent the need to specify the identity of true risk factors and devise a more powerful methodology for detecting the role of firm fundamentals in determining firm-specific risk exposures.

The tests require knowledge of the factor structure of expected returns. However, there is no widely accepted theory that produces an empirically validated factor structure. Single-factor models such as the Capital asset pricing model (CAPM) and the consumption-based CAPM (CCAPM) have notoriously failed to describe average returns, while they are based on relatively non-controversial theories (Mankiw and Shapiro 1984; Breeden et al. 1989; Fama and French 1992, 1993, 1996).[56] Merton's (1973) intertemporal CAPM (ICAPM) and Ross's (1976) arbitrage pricing theory (APT) allow for multi-factor structure for expected returns but provide little guidance on the *a priori* identity of additional risk factors. The investment-based q-factor models proposed in Hou et al. (2015) and others are not theoretically consistent with covriance risk models.[57] Leading models in empirical work such as Fama and French's (1992) three-factor model and Fama and French's (2016) five-factor model are empirically motivated and there is no safeguard to ensure that the

[56]It may also be argued that the failure of CAPM or CAPM are simply 'anomalous'.There is also an emerging literature that seems to produce a more sanguine picture of the performance of consumption based CAPM (Jagannathan and Wang 2007; Hansen et al. 2008; Dittmar and Lundblad 2017), but the evidence is limited to low-frequency returns and consumption data.

[57]Hou et al. (2015) acknowledge that their four-factor asset pricing model is silent on why investment-driven expected returns are due to covariance risks. In fact, Lin and Zhang (2013) argue that investment-based asset pricing gives rise to characteristics-based rather than covariance-based expected return representations.

specified factors capture the true factor structure well.[58] Yet another class of potential risk factors is identified from a large and growing macro-finance literature, where the risk factors are important macroeconomic variables (Aretz et al. 2010; Lettau and Ludvigson 2001; Cochrane 2005, 2017). Although macroeconomic factors are important for developing understanding of the nature of risks, they are often poorly measured (e.g. consumption data) relative to return-based factors and not available at high frequency, and their explanatory power for stock returns are usually even much lower (Cochrane 2005, 1996).

To circumvent these issues, I follow Clarke's (2016) approach for identifying the 'data-implied' factor structure of expected returns, without selecting risk factors on an *a priori* basis. This methodology identifies the factor structure by extracting systematic co-movements in the cross-section of stock returns using principal component analysis (PCA). Although this approach does not *explain* the deep fundamentals of co-variance risk, it is very effective in *describing* the behavior of stock returns, which is sufficient for my purpose. The distinguishing feature of the Clarke (2016) factor model from other PCA-based factor models (e.g. those used in Kozak et al. (2018) and Zhang (2009)) is that the former identifies only systematic return comovements that are priced *ex ante*, which is better aligned with my purpose of examine how firm fundamentals are related to systematic risks.

Having identified the empirical factor structure of stock returns, I test whether the associations of firm fundamentals with the risk factor betas explain their return predictive ability. The tests build on a simple intuition: if a firm fundamental variable forecasts return through covariance risks, then its return predictive coefficient must vary over time along with factor risk premiums. For instance, if the variable positively predicts return only because it is positively associated with a covariance risk factor, then the predictive coefficient

[58] Fama and French (2016) suggest that the empirically motivated risk factors are likely to be combinations of multiple latent 'true' factors. Thus it is difficult to provide tight theoretical motivations to identify these factors.

must be higher (lower) when the factor realization is expected to be higher (lower).

I develop a novel two-step methodology to carry out the test. Specifically, I instrument both alphas and factor betas as linear functions of firm fundamentals. The test first obtains a time-series of the average return predictive coefficients of the firm fundamentals using monthly cross-sectional regressions. The second step then tests whether the time variation of the first-step predictive coefficients can be explained by the time variation of factor realizations. To facilitate the interpretation of the results, I devise a simple 'alpha ratio' that measures the extent to which the predictive coefficient of a variable is attributed to its contribution to alphas.

The test results are strikingly unfavorable to the notion that firm fundamentals proxy for covariance risks. The return predictive coefficients of many firm fundamentals examined in this study are poorly associated with factor realizations. The alpha ratios are often close to, or even greater than, 100%, suggesting that the associations of firm fundamentals with factors betas fail to explain a meaningful fraction of the return predictive coefficients of these firm fundamentals.

These findings suggest that characteristics-based firm-level expected returns should be used and interpreted with caution. For the purpose of constructing effective trading strategies or statistically robust forecasts of stock returns as in Lewellen et al. (2015), one can safely abstract away from the alpha-versus-beta tension and select a characteristics-based model that performs the best out-of-sample. However, if the purpose is to infer market perception of firms' systematic risks as in Penman and Zhu (2014), the characteristics-based expected return measures may not be valid risk proxies.

My study contributes to the literature by highlighting the missing link between characteristics-based expected return measures and covariance-based asset pricing principles. A closely related study in this spirit is Dittmar and Lundblad (2017), who find that firm fundamentals are associated with firm-specific betas with aggregate consumption growth, but the associations of some key fundamental variables such as book-to-market and asset growth are inconsistent with their respective return predictive coefficients. My approach differs in two important ways. First, I abstract away from the contentious identity of the underlying risk factors (without explicit reference to consumption risk) by using empirically extracted principal component factors. Second, my testing methodology evaluates the *quantitative* importance of contributions to alphas and betas for each firm fundamentals, whereas Dittmar and Lundblad (2017) focus only on the *qualitative* associations of firm fundamentals with risk factor betas.

This chapter proceeds as follows. Section 3.2 details the research design, including the methodologies for extracting systematic risk factors and testing associations of firm fundamentals with covariance risks. Sections 3.3 describes the sample and variable definitions. Section 3.4 reports the empirical results. The final section summarizes this chapter.

3.2 Research design

My research design involves two key elements. First, I empirically identify the factor structure of the cross-section of stock return. Second, I check whether the ability of firm fundamentals to predict stock returns is due their associations with firm-specific exposures to covriance risk factors.

3.2.1 Identifying covariance risk factors

Researchers have found many firm fundamentals that forecast stock returns, and stocks with similar fundamentals tend to move together. However, return co-movements are not necessarily systematic and may not constitute priced risk (e.g. Gerakos and Linnainmaa 2014). Thus, traditional market-wide risk factors, which are usually constructed as returns on long-short portfolios formed on the basis of firm characteristics, are not guaranteed to be systematic risk factors.[59] Also, there is no guarantee that the combination of constructed factors explains all important sources of systematic co-movements in the cross-section of stock returns.

To avoid the above issues with traditional factors constructed from firm characteristics, I follow Clarke (2016) procedure based on principal component analysis (PCA) to identify statistical co-movements in realized stock returns on portfolios sorted by an *ex ante* signal for predictable stock returns. This approach has the advantage that only systematic sources of return co-movements will be identified as risk factors, and usually almost all the economically important elements of return co-movements will be absorbed by the first few principal component factors.

This procedure can be summarized in three steps. First, I run a cross-sectional regression model to estimate the relation between monthly excess stock return on a large set of firm characteristics that have been shown to predict returns. Second, I combine the regression coefficients estimated from a 12-month rolling hold-out sample and lagged firm characteristics to generate estimates for *ex ante* expected returns, and then I sort the stocks in the cross-section into 25 equal-size portfolios. Finally, I use principal component analysis technique to extract data-implied risk factors that explain the variations of one-month-ahead *realized returns* of the 25 predicted-return-sorted portfolios.[60] Clarke (2016) shows that this PCA-based approach provides a very stable description of the variance-covariance matrix of monthly stock returns.

[59]Gerakos and Linnainmaa (2014) find that Fama and French's (1992) high-minus-low (HML) factor, which is constructed as the return on a portfolio longing high book-to-market and shorting low book-to-market stocks, is contaminated by some non-systematic return co-movements.

[60]The focus on monthly stock returns is common in most asset pricing studies. Although some studies (e.g. Kozak et al. (2018)) use daily returns, this would not be meaningful for my purpose as many return predictors at the firm level do not vary enough on the daily basis.

The key step in this procedure to ensure that only systematic risk factors are extracted is to form expected-return-sorted portfolios of stocks. The reason for using portfolios instead of individual stocks is that common risk factors may be swamped by idiosyncratic noise or non-systematic factors at the individual stock level. Focusing on portfolio returns allows these irrelevant sources of return variations to be cancelled out, so that only important common co-movements in the cross-section stand out. Indeed, Zhang (2009) shows that the principal components extracted from individual stocks have little explanatory power for the cross-sectional variation in stock returns. The portfolio sorts are performed on the basis of *ex ante* estimates of expected returns, because the return co-movements that are not *ex ante* priced in expected returns are not systematic (Clarke 2016). Sorting stocks by expected return estimates prevents these unpriced return co-movements to affect the extracted risk factors. Other PCA-based factor models (e.g. those used in Kozak et al. (2018)), in contrast, allow non-priced co-movements to show up as relevant risk factors.

To obtain estimates for *ex ante* expected returns, I draw on a large set of return predictors including many firm fundamentals and market-based characteristics that have been shown to predict one-month-ahead stock returns. Arguably, the factor structure identified may be different if the researcher adds more return predictors to sort expected returns. However, introducing new predictor variables can change the empirical risk factors only if they have strong predictive information *independent* of that contained in the existing set of return predictors. Green et al. (2016) examine 94 variables and find that only a few provide independent information about returns. Since these independently significant return predictors are already in my expected return estimation, I regard the data-implied factor structure as robust to additional return predictors.

Although this approach for identifying covariance risk factors does not *ex-*

plain the deep economic fundamentals of risk factors, it is very effective in *describing* the empirical behavior of stock returns, which is sufficient for my purpose. The central question investigated in this study is whether firm fundamentals that predict future returns are associated with priced covariance risk, but the general equilibrium source of the covariance risk is not important. Nevertheless, the results in Clarke (2016) and Dittmar and Lundblad (2017) together show that the risk factors generated in this approach seem to mimic aggregate consumption growth, consistent with consumption-based asset pricing theories.

A potential limitation of this approach is that it may not pick up stock return co-movements that are less pervasive in the cross section or associated with low risk premiums, because 'non-principal' components of return co-movements are dropped from the identified factor structure. It is still possible that some of these 'non-principal' components are true systematic and priced risk factors. However, if a firm fundamental variable is associated with such a factor, the practical importance of the variable for *ex ante* risk assessment is unlikely to be economically meaningful. Therefore, I argue that there is no significant loss from focusing only on principal components (PC) factors of stock return co-movements.

3.2.2 Testing associations of firm fundamentals with covariance risk factors

Given a determined factor structure, the second key step of my analysis is the test of the associations of firm fundamentals with the risk factors. The standard approach to perform such a test is developed in Fama and MacBeth (1973) and illustrated iconically by Fama and French (1996). They first estimate risk factor betas (i.e. 'standardized' covariances with risk factors) for each portfolios sorted by a variable and then check (i) whether the variable is consistently associated with the estimated risk factor betas and (ii) whether controlling for the factor betas 'drives out' the predictive power of the variable. Specifically, the test runs the following *time-series* regression to estimate factor betas $\beta_i^k, k = 1, 2, \ldots, K$:

$$R_{it+1} = \alpha_i + \sum_{k=1}^{K} \beta_i^k f_{t+1}^k + \epsilon_{it+1} \tag{3.1}$$

$$\text{where} \quad \mathbb{E}_t[\epsilon_{it+1}] = 0$$

for each test asset i, where R_{it+1} is the return of the test asset i and f_{t+1}^k is a vector of the covariance risk factors. α_i (the 'alpha') is the predictable non-risk component of returns on asset i, which should be zero if the factor model is true. If a variable predicts stock returns simply because it proxies for covariance risks, then the betas should be associated with the variable in a manner consistent with its association with returns, and the intercept α_i should exhibit no relation with the characteristic.

Fama and French (1996) apply this method to a range of firm fundamentals including book-to-market, size and sales growth and conclude that the predictive power of these variables is consistent with, and driven out by, their associations with Fama and French (1993) three-factor betas. For instance, they find that sales growth is highly positively associated with the loadings on the 'high-minus-low' factor (HML), and the alphas are insignificantly different from zero. Thus they conclude that the 'sales growth anomaly' is explained by covariance risks but not mispricing. This testing approach has been followed by Fama and French (2016) and Hou et al. (2015).

However, this testing approach implicitly assumes that the risk factor betas and the non-risk component of returns are constants, or it ignores the role of conditioning information for capturing potential time-variation of the alphas and betas. Thus, I label this approach as the *unconditional test.* If the alphas and betas are indeed time-varying (i.e., the 'investment opportunity set' changes over time), and the firm fundamentals that predict returns are 'state variables' that proxy for rational forward expectations for the *conditional* alphas and betas, then the unconditional test may not be powerful enough to detect meaningful associations of the characteristics with the alphas and betas (Lewellen and Nagel 2006).

This latter observation motivates the following innovative *conditional test*, which allows the firm fundamentals to serve as potential proxies for both forward alphas and betas. Specifically, let X_{it} denote a vector of firm fundamentals. I make the following assumption about the cross-sectional variation in stock returns in excess of spot interest rates:[61]

$$R^e_{it+1} = \alpha_{it+1} + \sum_{k=1}^{K} \beta^k_{it+1} f_{kt+1} + \epsilon_{it+1} \tag{3.2}$$

$$\begin{aligned} \text{where} \quad \alpha_{it+1} &= \bar{\alpha} + a' X_{it} + \epsilon^{\alpha}_{it+1} \\ \beta^k_{it+1} &= \bar{\beta}_k + {b_k}' X_{it} + \epsilon^k_{it+1} \\ \mathbb{E}_t[\epsilon_{it+1}] &= \mathbb{E}_t[\epsilon^{\alpha}_{it+1}] = \mathbb{E}_t[\epsilon^k_{it+1}] = 0 \\ \mathbb{E}_t[\epsilon^k_{it+1} f^k_{t+1}] &= 0 \end{aligned}$$

Note that both the alpha and beta are potentially predictable by the vector of firm fundamentals X_{it}. Thus, the cross-sectional variation in expected returns inherits the cross-sectional variation in firm fundamentals. This approach effectively decomposes the predictive power of X_{it} for returns into two components: one that proxies for covariance risks (betas) and one that is due to mispricing (alphas). It facilitates explicit *quantitative* evaluation of the rel-

[61]Spot interest rates are measured using one-month T-bill rates obtained from Federal Reserve through WRDS connections.

ative importance of alpha-based and beta-based explanations for the return predictive ability of the firm fundamentals in questions.

Instrumenting alphas and betas using X_{it} leads to a more powerful test than the traditional Fama and French (1996) test for detecting the role of firm fundamentals in determining firm-specific alphas and betas. To illustrate this point, consider a simple thought experiment. Suppose x_{1t} and x_{2t} are two firm fundamental variables that both highly positively contribute to the firm's beta with respect to a risk factor, but x_{1t} and x_{2t} are negatively correlated in the data. A Fama and French (1996) test based x_{1t}– or x_{2t}–sorted portfolios might produce a week pattern in the factor beta, if the correlation between x_{1t} and x_{2t} causes the information about beta contained in the two variables to cancel out on average. By contrast, estimating the instrumented beta representation in (3.2) would detect a stronger positive associations of x_{1t} and x_{2t} with the factor beta.[62]

While it has become a standard practice to specify instrumented time-varying beta processes to test conditional asset pricing models (Harvey 1989; Zhang 2005; Cochrane 1996; Dittmar and Lundblad 2017), the process of alpha is often left unspecified. In these 'beta-only' tests , rejection of the hypothesis that alphas are zero is regarded as evidence that systematic mispricing exists. But *is there some alpha driven by some specific firm fundamentals? Do some firm fundamentals incrementally contribute to alphas in the presence of others?* Linking X_{it} explicitly to α_{it+1} allows for more powerful tests to address these questions. For instance, if x_{1t} and x_{2t} in the thought experiment are also associated with large positive contributions to alphas, a 'beta-only' test may not suggest large mispricing, again due to the negative correlation between x_{1t} and x_{2t}. However, there may be some sizable alpha to gain by combining the x_{1t} and x_{2t} simultaneously. This possibility would be revealed

[62] Admittedly, Fama and French (1996) approach can be adapted to multivariate conditionally sorted portfolios to control for other variables, but this is difficult to implement if there is a large array of potential control variables.

if x_{1t} and x_{2t} are used as instruments for α_{it+1}. Similarly, it is also possible that a significant alpha can be detected, but the alpha is not associated with any of the variables included in X_{it}. My testing framework is able to pick up this case while the 'beta-only' tests may not.

Given there is very little theoretical guidance in the literature on how firm fundamentals relate to return distributions, the functional forms connecting firm fundamentals to alphas and betas are chosen to be linear as only a plausible first approximation. In principle, the functional form can be motivated by studying a general equilibrium investment-based models such as those in Cochrane (1996), Zhang (2005) and Lin and Zhang (2013), but these models do not accommodate a wide range of firm firm fundamentals simultaneously and are often based on assumptions made to ensure analytic tractability.

The additional assumption $\mathbb{E}_t[\epsilon^k_{it+1} f^k_{t+1}] = 0$ in equation (3.2) implies that the firm in question is able to predictably adjust its forward risk exposure only through altering the firm fundamentals in question. In principle, this product $\mathbb{E}_t[\epsilon^k_{it+1} f^k_{t+1}]$ can be non-zero and seen as an element of 'estimation risk', that is, the systematic portion of the uncertainty regarding forward-looking betas. Lewellen and Nagel (2006) provide indirect evidence that this assumption seems to inconsequential. Thus, I impose this assumption for simplicity.[63]

An important feature of the new conditional testing model is its ability to evaluate the relative importance of the alpha-versus-beta elements of the explanatory power of firm fundamental variables for future returns, because the testing framework models alphas and betas on equal footing. It is quite plausible that the same variable not only carries information about covariance risks but also contributes to investors' information processing errors, trading frictions and/or non-market forces that may induce alphas. The relative importance of alpha and beta contributions of the firm fundamental variable

[63] In unreported tests, I also find that the average values of $\epsilon^k_{it+1} f^k_{t+1}$ calculated using regression residuals of factor betas on firm fundamentals are almost negligible.

can help guide the search for deeper sources of its predictive power for returns.

The presence of pure time-series variables f_{kt+1} in model (3.2) poses a challenge for estimating the model parameters, because they carry no cross-sectional variation. To implement the test, I design a two-step methodology. First I rewrite equation (3.2) as the following cross-sectional earnings forecasting model:[64]

$$\mathbb{E}_t[R^e_{it+1}] = (\bar{\alpha} + \sum_{k=1}^{K} \bar{\beta}^k \gamma_t^k) + (a + \sum_{k1}^{K} \gamma_t^k b^k)' X_{it} \tag{3.3}$$

$$\text{where} \quad \gamma_t^k = \mathbb{E}_t[f^k_{t+1}]$$

Note that equation (3.3) is conditional on time-t information, thus it cannot be estimated in the time-series. Hence the traditional two-pass testing method for asset pricing models is not applicable.[65] However, given a particular t, equation (3.3) can be estimated in the cross-section. Specifically, I regress one-period-ahead excess returns R^e_{it+1} on X_{it} for each month:

$$R^e_{it+1} = \delta_{0t} + \delta'_{1t} X_{it} + \epsilon_{it+1} \tag{3.4}$$

It is apparent by matching the coefficients between equations (3.3) and (3.4) that $\delta_{0t} = \bar{\alpha} + \sum_{j=1}^{K} \bar{\beta}^k \gamma_t^k$ and that $\delta_{1t} = a + \sum_{j=1}^{K} \gamma_t^k b^k$. However, the underlying model primitives $\bar{\alpha}$, $\bar{\beta}$, a and b^k are not identified in this step. The

[64] The algebra is shown in Appendix B.

[65] The traditional two-pass method can be summarized as follows. Consider a typical asset pricing model $R_{it+1} = \alpha_i + \beta_i f_{t+1} + \epsilon_{t+1}$. Note that β_i only varies across firms, and f_{t+1} varies over time. First run time-series regressions for each asset i to obtain estimates for β_i, $\hat{\beta}_i$, then use the estimates $\hat{\beta}_i$ as the regressor in a second-pass cross-sectional regression to examine how the factor f is priced.

first-step regression is not different from standard cross-sectional return forecasting regressions commonly used in the anomaly literature.

The first-step estimation produces a time-series of estimates $\hat{\delta_{0t}}$ and $\hat{\delta_{1t}}$, but of central interest is the information conveyed by coefficients of b_k and a. Exploiting the assumed constancy of of b_k and a, I recover these parameters by a second-step time-series regression of $\hat{\delta_{0t}}$ and $\hat{\delta_{1t}}$ on forward factor realizations f^k_{t+1}:[66]

$$\begin{aligned}
\hat{\delta_{1t}} &= a + \sum_{k1}^{K} b_k{}' f_{kt+1} + u_{1t} \\
\hat{\delta_{0t}} &= \hat{\alpha} + \sum_{k1}^{K} \bar{\beta}_k{}' f_{kt+1} + u_{0t}
\end{aligned} \tag{3.5}$$

with u_{1t} and u_{0t} being zero-mean error terms.

The second-step regression with regressand $\hat{\delta_{1t}}$ answers the question: *how much of the predictive ability of the fundamental variable(s) X_{it} is attributable to its contribution to betas (or alphas)?* The test carries the intuition that if the cross-sectional predictive ability of firm fundamentals for stock returns is due to their associations with covariance risks (factor betas), then their predictive coefficients must vary over time in response to the expected realization of the risk factor. For instance, if a firm fundamental variable z_{it} forecast higher stock returns R^e_{it+1} because z_{it} is positively associated with the firm's beta on a risk factor f_{kt+1} that has a positive risk premium, then the predictive coefficient of z_{it} must be higher (lower) when the f_{kt+1} is expected to be higher (lower).

The tests of the associations of firm fundamentals with factor betas are simply standard tests of the coefficients b_k with the null hypothesis $b_k = 0$. The test

[66]Note that the following step is not trivial, although the algebra is simple. The demonstration is provided in Appendix B.

for the contribution of firm fundamentals to alphas is captured by the coefficients a. Auxiliary results regarding $\hat{\alpha}$ and $\bar{\beta}^k$ are also of potential interest. If the characteristics are cross-sectionally demeaned, then $\bar{\alpha}$ and β^k capture unconditional alphas and betas respectively. Evidence of $\bar{\alpha} \neq 0$, then it indicates presence of mispricing unrelated to the firm fundamentals included in the test.

A few points are worth noting. First, the estimation of equations (3.5) assumes there is some time-variation in parameters δ_{1t} and δ_{0t}, but it does not require their estimates $\hat{\delta_{1t}}$ and $\hat{\delta_{0t}}$ to be statistically significant in the first-stage regressions.[67] My focus is to test if the time-variation of the cross-sectional return predictive coefficients can track the time-variation of *ex post* factor realizations, but the average magnitudes of the cross-sectional return predictive coefficients are not central. For instance, a firm fundamental variable can positively predict returns in bad times but negatively predict returns in good times. The first-stage regression coefficient would be insignificant, but this variable may still play an important role in determining the firm-level exposures to time-varying risk factors. Second, the coefficients b_k may take either positive or negative values, depending on whether the respective firm fundamental variable is increasing or decreasing in the risk exposure. Since the PC factor model used is silent about the nature of the underlying risks, I do not impose *a priori* restrictions of the signs of the second-stage regression coefficients.

3.3 Data and variable definitions

My sample consists of monthly observations of US stocks traded in the AMEX, NYSE and NASDAQ exchanges from January 1980 to December 2016. I obtain stock market data from CRSP and annual accounting data from Compu-

[67] In fact, Harvey et al. (2016) show that many return predictors are not as significant as reported by prior studies.

stat. Since stock returns are measured at monthly frequency while accounting data are measured at annual frequency, I align the latest accounting data with each monthly observation of stock returns by assuming a four-month lag from the firm's financial year end.[68] For instance, the return over May 1999 for a December financial year end firm is aligned with accounting data for financial year 1998, while the return over March 1999 of the same firm is aligned with with accounting data for financial year 1997.

I select a wide range of 19 return predictors to form *ex ante* expected return estimates. The set of characteristics differs from leading recent studies on the combined predictive ability of firm characteristics for stock returns. Lewellen et al. (2015) select 15 return predictors and focuses on the out-of-sample predictive performance of characteristic estimates of expected returns. Green et al. (2013) and Green et al. (2016) examine the dimensionality of cross-sectional expected returns and thus consider 60 and 94 characteristics respectively. The use of the return predictive model in this study is to generate a large spread in portfolio returns. The selection of characteristics is a balanced consideration of the need to generate large enough spreads in expected returns while maintaining reasonably well populated portfolios to allow non-systematic risk factors to 'average out' within the portfolios. Thus, the set of characteristics should be large enough to capture a large portion of the cross-sectional variation in returns but modest enough to avoid overly restrictive data availability requirements.

In addition, I consider both accounting-based and market-based characteristics as return predictors. Including market-based characteristics adds signals for future returns that complement the information in the firm fundamental variables, and thus will generate a more complete description of expected returns and potentially more accurate identification of covariance risk factors. I do not use return predictor variables that cannot be constructed from CRSP

[68] This choice assumes that the accounting data for a particular financial year are available to investors four months after the financial year end.

or Compustat data to avoid further data restrictions.[69] Table 3.1 provide detailed definitions of the return predictors used to construct expected return estimates.

Table 3.1: Definitions of cross-sectional predictors of one-month-ahead stock returns

Predictor	Notation	Definition
Firm fundamentals		
Book-to-market	$LogBM_t$	Natural logarithm of book value of equity divided by $Mcap_t$ (defined in this table). Book value of equity is common equity(Compustat item CEQ) plus preferred treasury stock (TSTKP) and minus preferred dividends in arrears (DVPA)
Cash holding	$Cash_t$	Total cash and cash equivalent (Compustat CHE) divided by total assets at the end of fiscal year
R&D intensity	RD_t	Research and development expense (Compustat item XRD) scaled by market capitalization at the end of fiscal year [70]

continued next page

[69]For instance, prior studies find that properties of analyst forecasts, short seller activity, executive compensation, credit rating, institutional holding, and corporate governance practices may predict stock returns. These variables require additional data from other sources. Green et al. (2016) document that these variables provide little information incremental to what is captured by the existing variables used in this study. Hence, I do not incorporate these variables in my analysis.

[70]Item XRD is often missing for firms that do not incur any research and development cost. I convert all missing values of XRD to zero to avoid dramatic loss of sample size.

Table 3.1 continued

Predictor	Notation	Definition
Accruals	Acc_t	The sum of changes in receivables (Compustat item RECT), inventory (INVT) and other current assets (ACO), less depreciation and amortization charges (DP) and changes in other current liabilities (LCO)
Asset growth	Agr_t	The natural log of total assets at the end of fiscal year minus the natural log of total assets at the end of the prior fiscal year
Financial leverage	Lev_t	Total financial debt divided by the book value of equity, where total financial debt is estimated by the sum of debt in current liabilities (Compustat item DLC) and debt in long-term liabilities (item DLT)
Investment in fixed assets and inventory	Inv_t	Sum of increments in the gross costs of property, plant and equipment and in inventory
Sales growth rate	Sgr_t	Percentage change in sales revenue from the prior to current financial year
Operating profitability	Opr_t	Total revenues (Compustat item REVT) less the sum of cost of goods sold (COGS) and selling, general and administrative expenses (XSGA), all scaled by market capitalization at the end of the financial year

continued next page

Table 3.1 continued

Predictor	Notation	Definition
Market capitalization	$LogMcap_t$	The natural log of the product of price per share (CRSP item PRC) and total number of shares outstanding (SHROUT) four months after the financial year end
Market-based characteristics		
Momentum change	$\Delta Mom6_t$	Changes in buy-and-hold returns over the last consecutive six-month rolling windows (i.e., $t-6$ to $t-1$ and $t-12$ to $t-7$)[71]
One-month momentum	$Mom1_t$	Cum-dividend stock return over the prior month $t-1$
One-year Momentum	$Mom12_t$	Buy-and-hold stock return accumulated from over the period $t-12$ to $t-2$
Turnover	$Turn_t$	Average monthly trading volume over the last three months ($t-3$ to $t-1$) divided by the total number of shares outstanding at the end of month t
Turnover volatility	$\sigma(Turn)_t$	Standard deviation of the ratio of daily trading volume over number of shares outstanding over the prior month $t-1$
Number of no-trading days	$Nztd_t$	Turnover-weighted number of days with zero trading volumes over the prior month $t-1$

continued next page

[71] All buy-and-hold returns are compounded using CRSP monthly stock file (MSF) and adjusted for delisting returns as per recommendations in Shumway (1997) and Shumway and Warther (1999)

Table 3.1 continued

Predictor	Notation	Definition
CAPM beta	$Beta_t$	Capital asset pricing model beta, estimated using up to 60 (minimum 24) lagged monthly stock returns
Net share issue	Nsi_t	The natural log of total number of shares outstanding (CRSP item SHOUT) at the end of fiscal year t minus the natural log of total number of shares outstanding at the end of fiscal year $t-1$.
Return volatility	Vol_t	Standard deviation of daily stock returns in February of year $t+1$, calculated using CRSP daily stock file (DSF)

Availability of the 18 return predictors restricts the sample size. Table 3.2 provide details of data availability for constructing these variables for three different size groups: 'Microcaps' includes stocks with market capitalizations below the 20th percentile of the NYSE sample distribution; 'Small firms' includes stocks with market capitalizations between the 20th and 50th percentiles; and 'Large firms' includes stocks with market capitalizations greater than the 50th percentile. The raw sample of monthly stock returns contains 2,014,986 observations. The final sample with all necessary data to estimate expected returns and implement PCA amounts to 1,514,252 observations over 444 months, which is about 25% smaller than the raw sample. Data availability problems of most return predictors are minimal for large firms, with most variables missing for only less than 3% of the total observations. For smaller firms, the percentages of observations with missing predictors are much higher for almost all predictors. Typically, market-based characteristics are better populated than firm fundamentals. For instance, among Microcaps, more

Table 3.2: Data availability of return predictors

Variable	Microcaps		Small firms		Large firms	
	%missing	#missing	%missing	#missing	%missing	#missing
$LogBM_t$	0.00%	-	0.00%	0	0.00%	-
$Cash_t$	15.94%	191,653	5.51%	22,672	1.85%	7,394
RD_t	0.00%	-	0.00%	-	0.00%	-
Acc_t	14.65%	176,200	14.41%	59,311	9.62%	38,524
Agr_t	8.50%	102,177	5.82%	23,945	2.08%	8,337
Lev_t	0.26%	3,134	0.35%	1,441	0.27%	1,088
Inv_t	10.56%	126,959	10.45%	43,014	6.95%	27,851
Sgr_t	10.14%	121,955	6.92%	28,488	2.25%	9,009
Opr_t	8.67%	104,318	6.37%	26,208	2.16%	8,637
$LogMcap_t$	0.00%	-	0.00%	-	0.00%	-
$\Delta Mom6_t$	9.30%	111,856	6.21%	25,563	2.44%	9,766
$Mom1_t$	0.00%	-	0.00%	-	0.00%	-
$Mom12_t$	9.30%	111,856	6.21%	25,563	2.44%	9,766
$\sigma(Turn)_t$	3.96%	47,652	2.50%	10,292	0.67%	2,697
$Turn_t$	4.71%	56,654	3.10%	12,775	0.91%	3,640
$Nztd_t$	4.11%	49,427	2.50%	10,294	0.67%	2,697
$Beta_t$	1.31%	15,796	0.81%	3,341	0.31%	1,230
Nsi_t	8.53%	102,584	5.86%	24,116	2.13%	8,523
Vol_t	0.00%	55	0.00%	2	0.00%	-

Notes: This table reports data availability of each of the return predictors defined in Table 3.1 for each size group. The '%missing' columns report the percentages of observations for which the return predictors are missing. The '#missing' columns report the numbers of observations for which the return predictors are missing. 'Microcaps' includes stocks with market capitalizations below the 20th percentile of the NYSE sample distribution; 'Small firms' includes stocks with market capitalizations between the 20th and 50th percentiles; and 'Large firms' includes stocks with market capitalizations greater than the 50th percentile.

than 10% of observations have missing values for $Cash_t$, Acc_t, Inv_t and Sgr_t , but all market-based characteristics are available for more than 90% of all observations.

Next, Table 3.3 presents the summary statistics of these return predictors for the mutually non-missing sample, which is used for constructing one-month-ahead return predictions. The statistics are largely consistent with those reported in various prior studies (e.g. Clarke 2016; Green et al. 2013; Harvey et al. 2016). A useful general observation is that market-based characteristics are much more variable than firm fundamentals. This is not surprising given that market data are more up-to-date than accounting data. Therefore, at monthly frequency, market-based characteristics may be better able to track stock return than firm fundamentals.

Table 3.3: Summary statistics of return predictors

Panel A: Firm fundamentals

	BM_t	$Cash_t$	RD_t	Acc_t	Agr_t	Lev_t	Inv_t	Sgr_t	Opr_t	$Mcap_t$
mean	0.703	0.158	0.064	-0.032	0.161	2.256	0.077	0.198	0.811	11.843
sd	0.644	0.203	0.111	0.131	0.451	4.847	0.183	0.617	1.146	2.235
p5	0.068	0.003	0.000	-0.241	-0.263	0.041	-0.114	-0.300	-0.216	8.353
p25	0.305	0.023	0.006	-0.083	-0.023	0.219	0.000	-0.018	0.314	10.230
p50	0.561	0.070	0.029	-0.028	0.071	0.649	0.037	0.090	0.626	11.727
p75	0.924	0.213	0.076	0.032	0.205	1.893	0.114	0.238	1.085	13.385
p95	1.861	0.637	0.251	0.164	0.865	10.172	0.386	0.918	2.519	15.699

Panel B: Market-based characteristics

	$\Delta Mom6_t$	$Mom1_t$	$\sigma(Turn)_t$	$Turn_t$	$Nztd_t$	$Beta_t$	$Mom12_t$	Nsi_t	Vol_t
mean	-0.001	0.010	4.186	1.081	1.404	1.086	0.129	0.116	0.034
sd	0.584	0.159	6.570	1.420	3.406	0.674	0.609	0.325	0.027
p5	-0.846	-0.229	0.344	0.071	0.000	0.135	-0.615	-0.064	0.009
p25	-0.264	-0.068	1.027	0.259	0.000	0.603	-0.213	0.000	0.017
p50	-0.005	0.000	2.133	0.594	0.000	1.011	0.051	0.008	0.026
p75	0.254	0.074	4.535	1.331	0.000	1.477	0.332	0.072	0.042
p95	0.872	0.271	14.835	3.717	9.947	2.330	1.127	0.936	0.088

Notes: This table reports the mean (row 'mean'), standard deviation (row 'sd'), the 5th, 25th, 50th, 75th and 95th percentiles (rows 'p5'-'p95') of each of the return predictors used to estimate expected returns. Panel A reports the statistics for firm fundamentals return predictors, and Panel B reports those for market-based characteristics. All variables are defined in Table 3.1.

3.4 Empirical results

3.4.1 Characteristics-based expected return estimates

The starting point of my empirical analysis is to estimate a return predictive model that generates a large spread in the cross-section of predictable stock returns. The model is a characteristic regression model. As in prior studies, I first estimate the mean model coefficients cross-sectionally with a lagged 12-month rolling hold-out sample and then apply the coefficient estimates to current characteristics to generated predicted returns (e.g. Fama and French 2008; Lewellen et al. 2015).[72]Fama and French (2008) show that many characteristics have differing predictive ability for stock returns for different size groups. Thus I run the regressions for the three size groups separately.

Regression estimates from the cross-sectional model for stock return predictions are reported in Table 3.4. The reported coefficient estimates are time-series means of 444 monthly cross-sectional regressions, and the t statistics are computed based on the time-series standard errors of the point estimates of cross-sectional regressions, and the time-series averages of adjusted R^2s are reported at the bottom of the table. I apply Newey and West (1987) adjustments to the time-series standard errors with eight lags.

The coefficients estimates reported in Table 3.4 are largely consistent with prior studies in the anomaly literature, but their magnitudes and significance are somewhat weaker because the coefficients now represent *incremental* predictive ability of the characteristics while controlling for others and the returns are of monthly frequency.[73] Out of firm fundamentals, book-to-market,

[72]The length of rolling hold-out sample is set to 12 because Lewellen et al. (2015) shows that it generates the best out-of-sample predictive ability. However, the results are not sensitive to this choice. Fama and French (2006) even argue that using the full-sample estimates instead of hold-out sample estimates is more appropriate if out-of-sample predictive ability is not the main concern, because the full-sample gives more precise estimates. In unreported analysis, I show that the results are robust to using the full-sample estimates.

[73]Many firm fundamentals are originally shown to forecast returns at annual or quarterly frequency (e.g. Sloan 1996). At higher frequencies, their predictive power are expected to

cash holdings, R&D intensity and operating profitability predict stock returns positively, and their predictive abilities seem pervasive across almost all size groups. Asset growth is negatively associated with realized returns mainly due to its predictive power for microcaps and small firms, and the negative predictive relation of financial leverage with returns is only significant among microcaps. Accruals, net operating asset growth and sales growth, however, are not significant in predicting one-month-ahead returns for any size group. On the other hand, the predictive power of market-based characteristics tend to be more pervasive and significant at monthly frequency than firm fundamentals, consistent with the findings of (Green et al. 2016), while their ability to forecast returns is typically much stronger among small firms and microcaps, except for the change in 6-month momentum. 1-month momentum, turn over volatility, size, and return volatility are significant across all size groups.

Harvey et al. (2016) argue that, due to the large sample sizes employed by empirical asset pricing studies, the relevance of many firm characteristics for return prediction is widely overstated and the hurdle for claiming a significant characteristic-return relation should be raised. Specifically, they suggest that the critical value for t-statistics of the return predictive coefficients should be at least 3. Indeed, given the higher hurdle, the number of significant characteristics for all firms is considerably reduced, and their predictive abilities are even more concentrated among microcaps. For large firms, only $\Delta Mom6_t$ remain significant.

be weaker because firm fundamentals are much more stable and persistent than market prices.

Table 3.4: Fama-Macbeth regression estimates for cross-sectional stock return prediction model

	All firms	Microcaps	Small firms	Large firms
Firm fundamentals				
$LogBM_t$	0.004***	0.004***	0.000	0.003**
	(3.9)	(3.47)	(0.18)	(2.26)
$Cash_t$	0.010***	0.010***	0.009**	0.007**
	(3.42)	(3.09)	(2.21)	(2.03)
RD_t	0.025***	0.024***	0.033**	0.031**
	(3.7)	(3.6)	(2.53)	(2.41)
Acc_t	-0.003	-0.002	0.005	-0.002
	(-0.85)	(-0.63)	-0.98	(-0.28)
Agr_t	-0.005***	-0.005***	-0.006***	-0.003
	(-3.85)	(-2.62)	(-3.54)	(-1.34)
Lev_t	-0.001***	-0.001***	-0.001	-0.001
	(-2.88)	(-3.16)	(-0.99)	(-1.01)
Inv_t	-0.004	-0.005	-0.008	0.002
	(-1.42)	(-1.30)	(-1.44)	0.57
ΔNOA_t	0	-0.003	0.001	-0.002
	(-0.02)	(-0.65)	0.16	(-0.46)
Sgr_t	0.000	0.000	0.001	0.002
	(-0.35)	(-0.33)	(0.45)	(0.8)
Opr_t	0.001***	0.001**	0.001***	0.002***
	(3.78)	(2.57)	(2.71)	(2.78)

continued next page

Table 3.4 continued

	All firms	Microcaps	Small firms	Large firms
$LogMcap_t$	-0.001*	-0.005***	-0.002*	-0.001*
	(-1.87)	(-4.91)	(-1.79)	(-1.70)
Market-based characteristics				
$\Delta Mom6_t$	0.001	0.002**	0.001	-0.003**
	(1.23)	(2.34)	(0.8)	(-2.05)
$Mom1_t$	-0.055***	-0.061***	-0.033***	-0.030***
	(-9.62)	(-9.26)	(-6.38)	(-4.95)
$Mom12_t$	0.004	0.005**	0.003	0.003
	(-1.64)	(-2.05)	(-1.39)	(-1.26)
$\sigma(Turn)_t$	0.001***	0.001***	0.001***	0.000*
	(5.44)	(5.77)	(4.19)	(1.85)
$Turn_t$	-0.006***	-0.008***	-0.005***	-0.002
	(-5.29)	(-5.76)	(-4.30)	(-1.59)
$Nztd_t$	-0.001**	-0.001***	-4030.5	-19172
	(-2.45)	(-4.15)	(-0.48)	(-1.14)
$Beta_t$	0.000	0.001	-0.001	-0.002
	(-0.07)	0.73	(-0.39)	(-0.91)
Nsi_t	-0.003***	-0.006**	-0.001	-0.001
	(-2.65)	(-2.57)	(-0.51)	(-0.95)
Vol_t	-0.122***	-0.174***	-0.158***	-0.151***
	(-3.58)	(-5.12)	(-2.73)	(-2.71)
$Cons$	0.023***	0.069***	0.039***	0.024***
	(3.49)	(5.84)	(2.81)	(3.07)

continued next page

Table 3.4 continued

	All firms	Microcaps	Small firms	Large firms
Adj R^2	0.064	0.054	0.096	0.152

Notes: This table presents time-series averages of monthly cross-sectional coefficient estimates of the regressions of one-month-ahead excess stock returns on the set of return predictors. All variables are defined in Table 3.1. Fama and MacBeth (1973) t-statistics with Newey and West (1987) adjustments with eight lags are provided in parentheses below the respective coefficient estimates. Adj R^2 is the time-series average adjusted R-squared of monthly cross-sectional regressions.

After obtaining monthly cross-sectional regression estimates, I compute firm-level expected return estimates using lagged 12-month average estimates and current firm characteristics included in the regression model. This construction uses only *ex ante* information observable to investors to form expected returns to avoid look-ahead bias. Then I sort stocks in the cross-section into 25 equal-size portfolios on the basis of their expected return estimates. Table 3.5 presents equal-weighted and value-weighted expected and realized one-month-ahead returns for the 25 expected-return sorted portfolios. By construction, equal-weighted (value-weighted) expected return estimates rises monotonically from -3.82 to 5.43 (-3.67 to 5.46) per month from the first to the 25th portfolio. While the spread in realized returns is much smaller (3.879 for equal-weighted returns and 2.421 for value-weighted returns), the monotonic ranking is largely preserved for both weighting schemes. On average, a zero-cost equal-weighted (value weighted) hedge portfolio generates a monthly return of 3.298 (1.892), which is statistically significant and economically large. Overall, evidence in Table 3.5 provides confidence that the expected return estimates do generate a large spread in realized returns.

3.4.2 Principal component risk factors

I use PCA to extract market-wide risk factors implied by the time-series co-movements of the returns on the 25 expected-return-sorted portfolios. This

Table 3.5: Summary statistics for expected-return sorted portfolios

	Equal-weighted		Value-weighted	
Portfolio	$\widehat{ER}_t$	R^e_{t+1}	$\widehat{ER}_t$	R^e_{t+1}
1 (low)	-3.826	-0.822	-3.669	-0.192
2	-2.182	0.250	-2.159	0.463
3	-1.472	0.578	-1.467	0.756
4	-0.993	0.536	-0.99	0.672
5	-0.641	0.607	-0.639	0.820
6	-0.393	0.954	-0.392	0.851
7	-0.133	0.819	-0.131	1.163
8	0.101	0.969	0.102	1.216
9	0.315	1.208	0.314	1.188
10	0.518	1.274	0.519	0.966
11	0.712	1.229	0.712	1.173
12	0.901	1.339	0.901	1.069
13	1.086	1.259	1.087	1.003
14	1.271	1.444	1.269	1.382
15	1.460	1.314	1.457	1.204
16	1.655	1.504	1.654	1.253
17	1.839	1.480	1.837	1.099
18	2.055	1.569	2.052	0.875
19	2.288	1.753	2.286	1.283
20	2.505	1.754	2.502	1.341
21	2.794	1.858	2.792	1.306
22	3.121	2.266	3.112	1.645
23	3.465	2.319	3.455	1.554
24	4.125	2.640	4.110	1.747
25 (high)	5.429	3.057	5.464	2.229
Average H-L		3.298		1.892
t-stat		7.760		4.087

Notes: This table reports equal-weighted and value weighted average excess returns of the 25 portfolios that are cross-sectionally sorted by the expected return estimates. The last two rows also report the averages and t-statistics of the equal-weighted and value-weighted returns on the hedge portfolios longing the 25th and shorting the 1st portfolios.

technique is effective only when there are strong correlations among these portfolio returns. Table 3.6 reports the correlation matrix of the returns on the 25 portfolios. All correlation coefficients are significantly positive at the 99% level, and the coefficients are very high, ranging from 0.54 to 0.95. This suggests that there is indeed a strong common co-movement component in the time-series variations of the portfolio returns.

In addition, Table 3.6 also shows that stocks with more similar expected returns appear to exhibit stronger co-movements. Specifically, the correlation coefficients between two portfolios in the vicinity of each other tend to be higher than those between two portfolios far apart. For instance, portfolio 2 (with the second lowest expected portfolio return) has correlations 0.91 and 0.95 with adjacent portfolios 1 and 3 respectively, but its correlations with portfolios 24 and 25 are much lower at 0.60 and 0.55 respectively. This implies that there are distinct covariance risk factors driving the cross-section of stock returns or that the risk factor loadings for high and low expected-return stocks are systematically different.[74] Note that since expected returns of the 25 portfolios are not affected by non-systematic covariance risk factors, the above preliminary evidence suggests that the differences in characteristics-based expected returns are indeed associated with differential systematic risk profiles.

[74] If there is only one risk factor, such as the market wealth portfolio in CAPM, and all stocks load similarly on the factor, then the correlations should not exhibit the pattern observed.

Table 3.6: Time-series correlations of returns on 25 expected-return-sorted portfolios

Low									Expected-return-sorted portfolios																High
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1																									
2	0.91																								
3	0.9	0.95																							
4	0.9	0.94	0.95																						
5	0.88	0.93	0.94	0.95																					
6	0.86	0.93	0.94	0.94	0.95																				
7	0.85	0.92	0.93	0.93	0.95	0.95																			
8	0.84	0.9	0.92	0.93	0.95	0.95	0.96																		
9	0.83	0.9	0.91	0.92	0.94	0.95	0.95	0.95																	
10	0.83	0.89	0.91	0.92	0.94	0.94	0.95	0.96	0.95																
11	0.81	0.87	0.89	0.91	0.93	0.93	0.94	0.96	0.95	0.96															
12	0.8	0.85	0.87	0.9	0.91	0.91	0.93	0.95	0.94	0.96	0.95														
13	0.78	0.83	0.85	0.88	0.89	0.9	0.91	0.93	0.93	0.94	0.95	0.96													
14	0.78	0.84	0.85	0.88	0.89	0.9	0.92	0.94	0.93	0.95	0.95	0.95	0.95												
15	0.75	0.79	0.81	0.85	0.86	0.86	0.89	0.9	0.9	0.92	0.93	0.94	0.94	0.95											
16	0.75	0.8	0.81	0.85	0.85	0.86	0.89	0.9	0.9	0.92	0.92	0.94	0.94	0.95	0.95										
17	0.73	0.78	0.79	0.83	0.83	0.84	0.87	0.88	0.88	0.9	0.91	0.93	0.93	0.94	0.95	0.95									
18	0.72	0.76	0.77	0.81	0.81	0.82	0.85	0.86	0.87	0.89	0.89	0.91	0.92	0.92	0.94	0.95	0.95								
19	0.68	0.72	0.73	0.77	0.77	0.78	0.82	0.83	0.83	0.85	0.86	0.89	0.9	0.91	0.93	0.94	0.95	0.95							
20	0.68	0.71	0.73	0.75	0.76	0.77	0.8	0.81	0.81	0.83	0.85	0.86	0.88	0.89	0.91	0.93	0.94	0.94	0.95						
21	0.67	0.69	0.7	0.73	0.74	0.74	0.78	0.78	0.78	0.8	0.81	0.84	0.85	0.86	0.89	0.91	0.92	0.93	0.94	0.95					
22	0.64	0.66	0.66	0.7	0.7	0.71	0.75	0.76	0.75	0.78	0.79	0.82	0.83	0.84	0.87	0.89	0.91	0.92	0.93	0.95	0.95				
23	0.6	0.6	0.61	0.62	0.62	0.63	0.67	0.67	0.67	0.7	0.72	0.74	0.76	0.77	0.81	0.84	0.85	0.87	0.89	0.92	0.94	0.94			
24	0.59	0.6	0.6	0.63	0.63	0.64	0.67	0.68	0.67	0.7	0.71	0.74	0.75	0.76	0.81	0.83	0.84	0.86	0.88	0.9	0.92	0.93	0.94		
25	0.55	0.55	0.54	0.57	0.58	0.59	0.63	0.63	0.62	0.66	0.65	0.68	0.69	0.7	0.75	0.76	0.78	0.79	0.81	0.84	0.86	0.87	0.91	0.9	

I perform (PCA) using the correlation matrix of the time-series of value-weighted returns of the 25 expected-return-sorted portfolios.[75] Table 3.7 shows that the co-movement in returns of the 25 portfolios can be very effectively summarized by only a few factors. The first principal component factor alone explains more than 85% of the variance of the portfolios. The eigenvalue of the correlation matrix diminishes very quickly, and the first three principal components are sufficient to explain more than 95% of the total variance. Figure 3.1 visualizes these observations. Thus, while we observe from Table 3.6 that there are distinct sources of return co-movements across the portfolios, there is a very strong factor structure in the return covariances: the number of factors needed to explain these co-movements may be quite small.

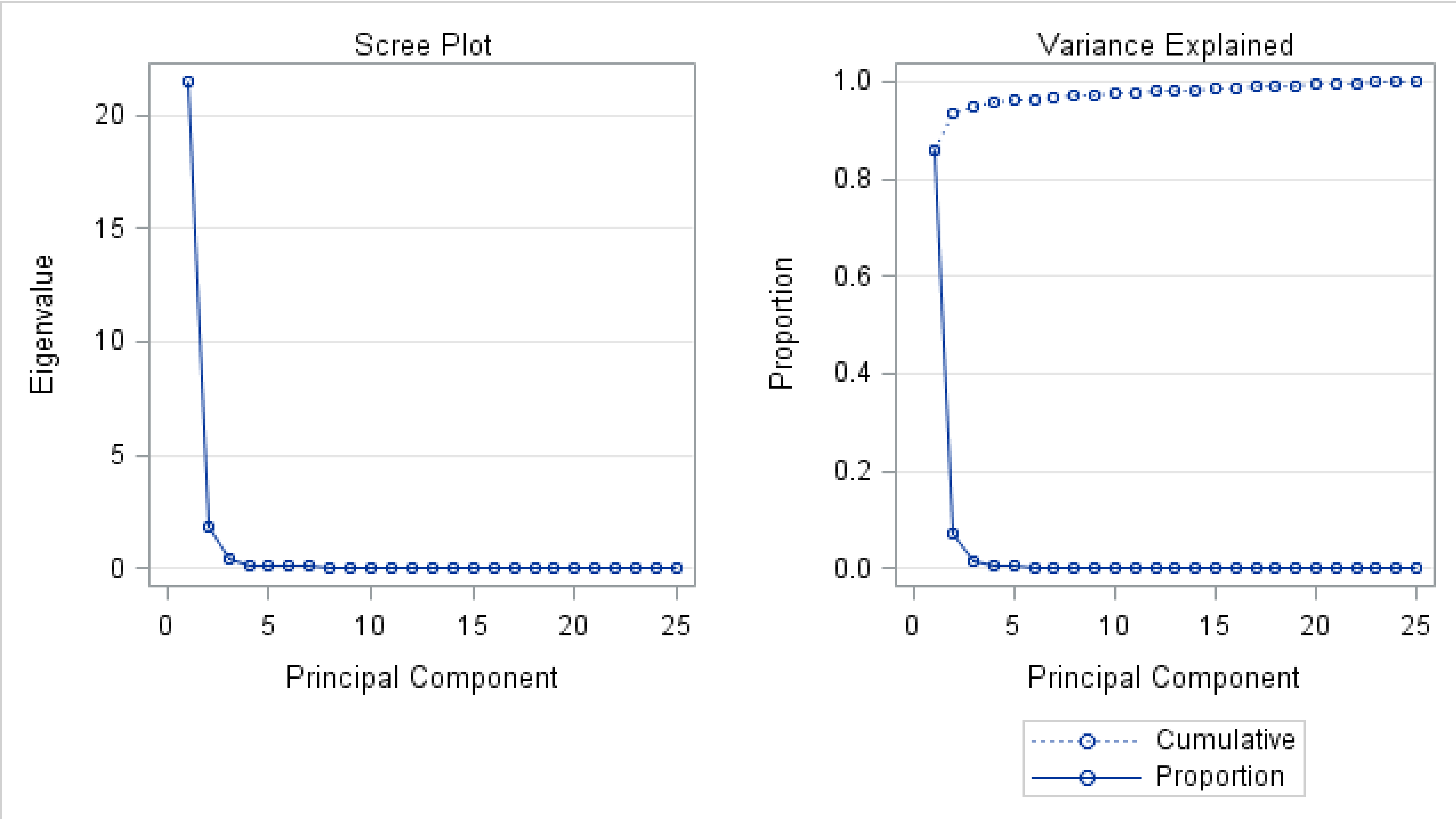
[75]PCA can also be implemented using the covariance matrix, but the number of principal component factors needed to explain the same amount of total variance-covariance is typically larger, although the results of subsequent analyses are not affected when more factors are used. I also replicate the PCA procedure using equal weighted portfolio returns, and the results are almost the same.

Table 3.7: Principal components of returns on the 25 expected-return-sorted portfolios

Principal components	Eigenvalues	% variance explained	Cumulative % variance explained
1	21.476	85.90%	85.90%
2	1.846	7.38%	93.29%
3	0.433	1.73%	95.02%
4	0.147	0.59%	95.61%
5	0.104	0.41%	96.02%
6	0.089	0.36%	96.38%
7	0.083	0.33%	96.71%
8	0.071	0.28%	97.00%
9	0.060	0.24%	97.24%
10	0.059	0.24%	97.47%
11	0.057	0.23%	97.70%
12	0.054	0.22%	97.92%
13	0.051	0.20%	98.12%
14	0.047	0.19%	98.31%
15	0.046	0.19%	98.50%
16	0.045	0.18%	98.68%
17	0.043	0.17%	98.85%
18	0.042	0.17%	99.02%
19	0.041	0.16%	99.18%
20	0.039	0.16%	99.34%
21	0.037	0.15%	99.49%
22	0.036	0.14%	99.63%
23	0.033	0.13%	99.76%
24	0.031	0.12%	99.88%
25	0.029	0.0012	100.00%

Notes: This table provides the basic summary statistics of the principal component analysis. The second column reports eigenvalues of the the correlation matrix of the one-month-ahead excess returns on the 25 expected return sorted portfolios. The third and fourth columns report the percentage and cumulative percentage of total variance of the one-month-ahead excess returns explained by the principal components.

Figure 3.1: Scree plot of excess returns on the 25 expected-return-sorted portfolios



Notes: This figure plots the eigenvalues, percentage of variance explained and cumulative percentage of variance explained for the principal components of the one-month-ahead excess returns on the 25 expected-return-sorted portfolios.

Next, Table 3.8 shows the eigenvectors of the first three principal component factors (PC factors). Since principal component factors are linear combinations of the 25 portfolios, thus they are portfolios themselves. The eigenvectors thus also give their respective portfolio weights on the 25 expected-return-sorted portfolios. This observation helps guide interpreting of the principal components. Given that PCA produces orthogonal PC factors, these weights can be interpreted equivalently, up to any positive scaling, as the factor loadings of the expected-return-sorted portfolios (Campbell et al. 1997). The first PC factor exhibits a flat loading pattern with a slight 'hump': its weighting on the portfolios remains similar from low to high expected returns, but it slightly weighs down extreme portfolios. The blue line in Figure 3.2 visually tracks the factor loading of the 25 portfolios on the first PC factor, which confirms the pattern.[76] This pattern implies that the first PC factor resembles the equal-weighted market portfolio. Intuitively, stocks tend to move up and down together regardless of their expected returns. Like the market excess return in CAPM, the first PC factor is expected to demand a positive risk premium.[77]

The second PC factor, in contrast, implies a long position on high expected-return portfolios and short position low expected-return portfolios. Equivalently, it suggests high expected return stocks tend to load heavily positively on the second PC factor, while low expected return stock move in the opposite direction. This pattern carries the intuition that realizations of some economic events may favor one part of the market and press the other, giving rise to cross-sectional differences in expected returns. For example, oil price hikes may drive up market expectations for the oil&gas industry but pose pressure on transportation firms, leading to high returns for the former and low for the latter. Note, however, the exact economic substance contributing

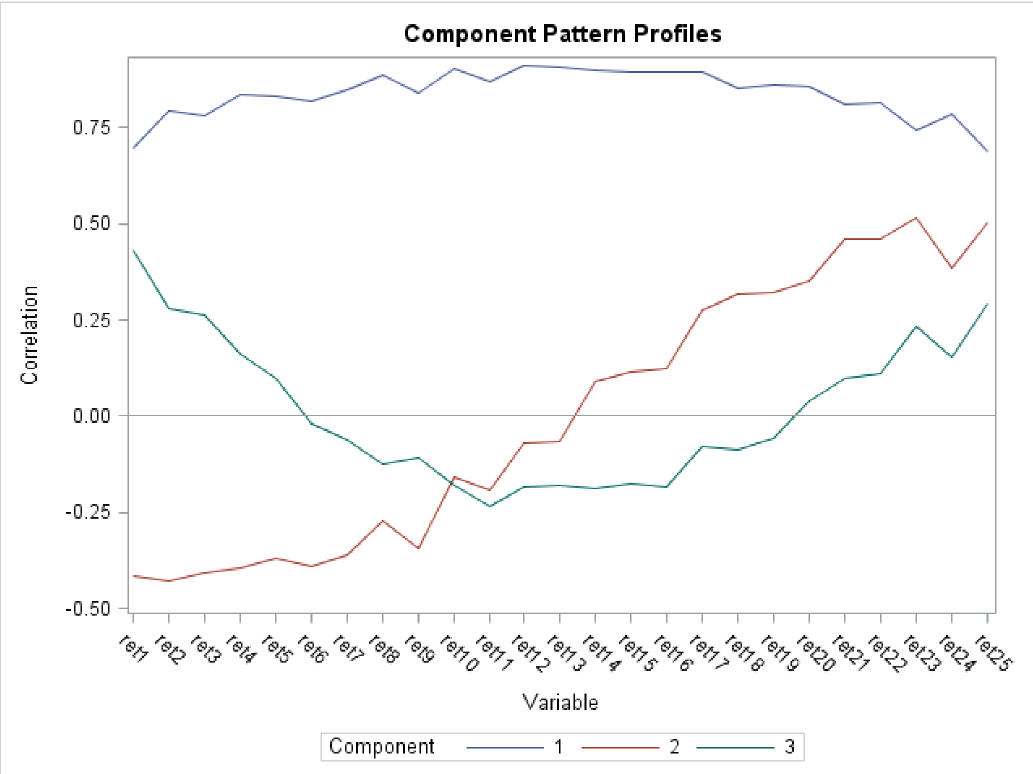
[76]The loadings are rescaled in Figure 3.2. This helps visual inspection but it does not alter the patterns. It simply shifts the curves up and down vertically.

[77]Since the PC factors are portfolio returns themselves, their respective risk premiums are the expected values of these portfolio returns.

to the second PC factor is not identified by PCA. By definition, high expected return stocks typically earn higher realized returns, thus the second PC factor should also receive a positive risk premium.

The third PC factor shows a bowl-shaped loading pattern. Both extreme high and low expected-return portfolios load positively on this factor, while stocks in the middle range load negatively. It captures the intuition that firms riding on the same market waves may end up with different expected returns. A plausible example is that firms may 'bet' on the same risky events, but there are expected winners and losers in these bets. On average, if investors dislike extremity, the expected risk premium for the third PC factor is negative.

Figure 3.2: Principal component factor portfolio weights



Notes: This figure plots the correlations of first three principal components and the one-month-ahead excess returns on the 25 expected-return-sorted portfolios. Horizontal labels 'ret1' to 'ret25' denote the the 1st to the 25th expected-return-sorted portfolios respectively.

Taken together, the co-movements in stock returns of the 25 expected-return-sorted portfolios exhibit a strong 'level-slope-curve' factor structure (Clarke 2016), which is a robust pattern that emerges in many other settings in asset pricing (Nelson 1987; Lord and Pelsser 2007; Afonso and Martins 2012; Mönch

Table 3.8: Principal component portfolio weights (scaled up by a factor of 10)

	Principal components		
Portfolios	1	2	3
1	1.832	-2.236	5.202
2	1.926	-2.434	3.173
3	1.951	-2.499	2.146
4	1.989	-2.161	1.584
5	2.013	-2.158	0.803
6	2.015	-2.072	0.309
7	2.052	-1.629	-0.104
8	2.058	-1.558	-0.779
9	2.040	-1.600	-1.206
10	2.082	-1.130	-1.274
11	2.073	-1.013	-1.875
12	2.089	-0.481	-2.004
13	2.077	-0.311	-2.355
14	2.091	-0.256	-2.186
15	2.076	0.510	-2.106
16	2.086	0.648	-1.560
17	2.084	0.988	-1.374
18	2.062	1.235	-1.173
19	2.034	1.685	-1.503
20	2.015	2.042	-0.345
21	1.971	2.505	0.691
22	1.950	2.663	0.623
23	1.848	3.317	2.075
24	1.854	3.060	2.087
25	1.664	3.867	3.381

Notes: This table presents the first three eigenvectors of the correlation matrix of the one-month-ahead excess returns on the 25 expected-return-sorted portfolios. All eigenvector elements are scaled by a factor of 10.

2012). Clarke (2016) further shows that the PC factor loading patterns extracted as above are very stable, in the sense that the first three PC factors extracted from two non-overlapping samples are almost perfectly correlated, suggesting that the factor structure is extremely robust out-of-sample and is a meaningful parsimonious summary of the co-movements in stock returns. These three PC factors explain almost all the variance in one-month-ahead returns on the 25 portfolios. Figure B.1 and Table B.1 provide the detailed loading patterns for all 25 PC factors. It is apparent that from the fourth PC factor onwards, the loading pattern becomes much noisier and less discernible. Hence, for subsequent analyses, I keep only the first three PC factors. Although it is possible that some systematically priced co-movements are captured by the omitted factors, I argue these co-movements (if any) are unlikely to be associated with economically significant risk premiums, because none of these principal components are meaningfully associated with expected returns.

Factor validation

Before applying the PC risk factors to test the associations between firm fundamentals and covariance risk, I perform a standard two-pass unconditional asset pricing test to validate the factors. Specifically, I first run time-series regressions of the returns of expected-return-sorted portfolios on the first three PC factors to obtain unconditional factor betas for each portfolio. Then in the second-pass, I regress the time-series averages of the portfolio returns on their respective first-pass estimates of the factor betas. To facilitate comparison, I repeat the same test using the Fama and French (1993) three-factor and Carhart (1997) four-factor models.

Table 3.9 reports the results of first-pass time-series regressions for the 25 portfolios. If the first three PC factors are the 'true' risk factors and if the APT holds, then the intercept α should be statistically indistinguishable from zero.

Of course, the PC factors are only approximate factors, thus some deviation of α from zero is expected. While stock returns are almost monotonically ranked across the portfolios, the alphas exhibit no clear pattern. The average absolute value of alpha estimate is $|\alpha|$ small, at only 18 basis point per month, and most alpha estimates are insignificantly different from zero. However, α estimates are still significant for some portfolios, and the largest absolute values of alphas are found for the two extreme portfolios: -0.78 and 0.42. This suggests that the factor model finds the most difficulty in pricing extreme portfolios. The R^2 and $\bar{R}^2$ are very high at around 0.85, suggesting the model estimates are quite precise. In comparison, Table B.2 shows that the average magnitude of alpha generated by Fama and French (1993) three-factor model is more than twice as large as that generated by the PC factor model. More than half of the alpha estimates are significantly different from zero. Results based on the Carhart (1997) four-factor model are shown in Table B.3. The inclusion of the momentum factor UMD considerably improves the model performance, cutting the average magnitude of alpha estimates by more than a half (0.20) to only slightly higher than that generated by the PC factor model. It can also be judged that the Carhart (1997) four-factor model performs better in pricing high expected return stocks, as indicated by the insignificant alpha for the 25th portfolio. However, it performs worse at the low extreme, as indicated, for example, by the -1.24 α for portfolio 1. The model fit of the four-factor model is somewhat lower than the PC model, although this is not of central concern for evaluating asset pricing models.

Table 3.9: Time-series regressions of 25 expected-return-sorted portfolio returns on the first three principal component factors

Portfolio	α	$t(\alpha)$	F_1	$t(F_1)$	F_2	$t(F_2)$	F_3	$t(F_3)$	R^2	$\bar{R}^2$	$\|\alpha\|$
1 (Low)	-0.78	-4.88	0.16	19.45	-0.30	-20.88	0.60	23.60	0.879	0.879	0.781
2	-0.10	-0.83	0.19	30.38	-0.28	-24.11	0.29	14.63	0.895	0.894	0.105
3	0.05	0.38	0.18	24.45	-0.24	-18.58	0.24	10.51	0.837	0.836	0.055
4	0.17	1.47	0.20	33.50	-0.23	-21.14	0.12	6.58	0.876	0.876	0.173
5	0.40	3.06	0.20	29.89	-0.21	-17.57	0.06	2.72	0.832	0.830	0.397
6	0.28	2.08	0.21	31.06	-0.22	-17.81	-0.06	-2.83	0.816	0.815	0.282
7	0.17	1.52	0.21	36.93	-0.18	-18.02	-0.09	-5.26	0.849	0.847	0.168
8	0.19	1.92	0.22	44.82	-0.14	-15.66	-0.14	-9.27	0.876	0.875	0.185
9	0.23	2.06	0.20	35.95	-0.17	-16.68	-0.13	-7.17	0.832	0.831	0.231
10	-0.09	-0.95	0.23	46.22	-0.08	-8.60	-0.18	-11.73	0.867	0.866	0.093
11	-0.06	-0.65	0.21	41.63	-0.09	-9.67	-0.21	-13.08	0.838	0.837	0.064
12	-0.14	-1.45	0.22	46.17	-0.03	-3.68	-0.17	-11.48	0.862	0.861	0.135
13	-0.02	-0.22	0.20	43.58	-0.03	-3.55	-0.16	-10.77	0.848	0.847	0.020
14	-0.16	-1.68	0.21	43.29	0.04	4.51	-0.17	-10.98	0.842	0.840	0.160
15	-0.31	-3.17	0.21	43.12	0.05	5.92	-0.16	-10.40	0.842	0.841	0.313
16	-0.02	-0.24	0.21	42.49	0.05	5.78	-0.16	-10.33	0.838	0.837	0.024
17	0.00	-0.03	0.20	45.31	0.13	15.66	-0.08	-5.76	0.871	0.871	0.003
18	-0.09	-0.80	0.21	37.83	0.15	15.38	-0.10	-5.54	0.826	0.825	0.088
19	-0.31	-2.92	0.21	38.80	0.16	16.28	-0.08	-4.84	0.837	0.835	0.307
20	-0.03	-0.28	0.20	37.29	0.18	18.70	0.01	0.75	0.849	0.848	0.029
21	-0.10	-0.97	0.20	36.39	0.25	26.30	0.06	3.71	0.866	0.865	0.103
22	0.08	0.78	0.19	37.12	0.25	27.31	0.08	5.19	0.876	0.875	0.079
23	0.13	1.09	0.17	28.29	0.32	29.17	0.22	11.66	0.860	0.859	0.130
24	0.14	0.95	0.19	25.78	0.23	17.59	0.13	5.67	0.782	0.780	0.137
25 (High)	0.42	2.40	0.19	21.24	0.43	26.77	0.41	14.85	0.831	0.830	0.421
Average									**0.849**	**0.848**	**0.179**

The second-pass cross-sectional regression results for all three factor models are reported in Table 3.10. The cross-sectional test relaxes the restriction that the risk premium of each factor should be equated to its average value, and a high cross-sectional R^2 is typically regarded as a measure of success of the factor model in question.[78] The factor betas of the first three PC factors explain 77.7% of the cross-sectional variation in stock returns, whereas Fama and French (1993) three factor betas explain only 68.2%. Carhart (1997) four-factor betas produce a comparable model fit as that of the three PC factor betas.

Also, consistent with expectation, the unconditional risk premiums of the first and second PC factors are positive, and the risk premium for the third is negative. The only highly significant factor beta is that of the second PC factor, with a large t-statistic 8.07. This suggests that the second PC factor F_2 is key in explaining the cross-sectional differences in returns.

Overall, the two-pass test results suggest that the factor structure identified from the PCA procedure is a good summary of returns and average returns. The PC factor model considerably outperforms Fama and French (1993) three-factor model, and it produces slightly lower pricing errors and slightly higher cross-sectional R^2 than the Carhart (1997) model.

[78] Lewellen et al. (2010) criticize the practice of applying this testing criterion to a small set of test assets on the grounds that it provides a low hurdle to claim success. However, Clarke (2016) conducts a set of extensive tests using 119 testing assets to validate a similar PC factor model and finds similar inferences. Since the main purpose of the paper is not to propose a new asset pricing model, detailed evaluation of the model performance is not included.

Table 3.10: Cross-sectional regressions of average 25 expected-return-sorted portfolios on factor betas

PCA factors			Fama French 3 factors			Carhart 4 factors		
	Estimate	t-stat		Estimate	t-stat		Estimate	t-stat
Cons	-1.100	-0.76	Cons	3.191	6.24	Cons	1.009	1.03
$\beta\ F_1$	8.924	1.24	$\beta\ R_m^e$	-2.473	-4.63	$\beta\ R_m^e$	-0.153	-0.15
$\beta\ F_2$	2.130	8.07	$\beta\ SMB$	0.351	0.90	$\beta\ SMB$	-0.333	-0.76
$\beta\ F_3$	-0.146	-0.27	$\beta\ HML$	-0.855	-0.93	$\beta\ HML$	-0.494	-0.59
						$\beta\ UMD$	1.207	3.67
R^2		0.777	R^2		0.682	R^2		0.759

Notes: This table reports results of the cross-sectional regression coefficients, t-statistics and R^2s of the three factor models using the 25 expected-return-sorted portfolios as the test assets. 'PCA factors' refers to the model with the first three principal components of the one-month-ahead excess returns of the 25 expected-return-sorted portfolios as the risk factors. 'Fama French 3 factors' refers to the Fama and French (1992) three-factor model, and 'Carhart 4 factors' refers to the Carhart (1997) four-factor model.

3.4.3 Firm fundamentals and covariance risks

In this subsection, I report and discuss the results on the associations of firm fundamentals with systematic covariance risks using the two-step method discussed in subsection 3.2.2. I conduct two sets of tests. First, I test each firm fundamental variable on an individual basis to examine whether firm fundamentals are individually associated with covariance risks. Second, I test the *joint* association of firm fundamentals with covariance risks and the *incremental* role of each variable in proxying for covariance risks.

Tests of individual firm fundamental variables

The first-step of the test is a set of cross-sectional regressions of one-month-ahead excess stock returns R^e_{it+1} on current firm fundamentals X_{it}. Its output is a time-series of 416 monthly estimates of the intercept δ_{0t} and slope δ_{1t}.[79] Table 3.11 reports the time-series averages of the first-step coefficient estimates, time-series averages of adjusted R^2, and Fama and MacBeth (1973) t-statistics when only one firm fundamental variable is included at a time. The predictive coefficients for the firm fundamentals are largely consistent with prior studies in the anomaly literature. Book-to-market (BM), operating profitability (Opr) and R&D intensity (RD) receive significantly positive coefficients, whereas asset growth (Agr), investments (Inv), size ($Mcap$) and sales growth (Sgr) receive significantly negative slopes.[80] Accruals (Acc), earnings yield (EP) and cash holding ($Cash$) receive the correct sign but are insignificantly different from zero. Leverage receives an insignificant positive coefficient, inconsistent with the anomalies literature but expected given the notion that leverage adds to risk.

[79] 28 months are lost for insufficient data to compute the PC factors.

[80] Note that all firm fundamentals are cross-sectionally standardized to have zero means and unit variances, so the coefficients represents the change in expected returns given one standard deviation increment of the variable.

Table 3.11: First-step cross-sectional regressions for individual firm fundamental variables

X_{it}	δ_1	$t(\delta_1)$	δ_0	$t(\delta_0)$	Adj R^2
Acc	-0.126	-2.690	0.896	3.324	0.22%
BM	0.299	5.728	0.867	3.279	0.43%
EP	0.056	0.632	0.867	3.279	0.74%
Opr	0.073	2.349	0.906	3.485	0.11%
RD	0.363	4.462	0.962	3.083	0.49%
Cash	0.125	1.558	0.889	3.362	0.61%
Agr	-0.410	-9.392	0.905	3.477	0.27%
Lev	0.059	0.944	0.869	3.290	0.45%
Inv	-0.356	-9.287	0.907	3.468	0.24%
Mcap	-0.193	-1.992	0.867	3.279	0.83%
Sgr	-0.244	-6.569	0.917	3.540	0.21%

Notes: This table reports results of the first-step cross-sectional regressions of firm-level one-month-ahead excess returns on individual firm fundamental variables. The reported estimates for δ_1 and δ_0 are time-series average estimates across the respective 416 monthly cross-sectional estimates. $t(\delta_1)$ and $t(\delta_0)$ are corresponding Fama and MacBeth (1973) t-statistics of δ_1 and δ_0 respectively, with Newey and West (1987) adjustments. The reported Adj. R^2s are time-series average adjusted R-squared of the respective 416 monthly cross-sectional regressions. *Acc* is accruals, *BM* is the book-to-market ratio, *EP* is earnings yield, *Opr* is operating profitability, *RD* is R&D intensity, *Cash* is cash holding, *Agr* is asset growth, *Lev* is financial leverage, *Inv* is investments, *Mcap* is market capitalization, and *Sgr* is sales growth. The variables are defined in Table 3.1.

Table 3.12 reports the second-step estimates of the time-series regression of the first-step predictive coefficient estimates $\hat{\delta_{1t}}$ on the first three PC factors:

$$\hat{\delta_{1t}} = a + b_1 F_{1t+1} + b_2 F_{2t+1} + b_3 F_{3t+1} + u_t$$

where $F_j, j = 1, 2, 3$ are the PC factors, and u is the zero-mean error term. The coefficients $b_j, j = 1, 2, 3$ measure the associations of the variable in question with the respective factor F_j, whereas a measures the contribution of the variable to predictable 'alphas' (i.e. mispricing). To facilitate interpretation, I report the 'alpha ratio' defined as a/δ_1 in the last column. It measures how much of the cross-sectional predictive ability of the firm fundamental variable is attributed to its contribution to alphas.

The results in Table 3.12 are striking. First, the time-series associations of the return predictive coefficients δ_1 with the first three PC factors are poor. The second-step R^2s ranges from 0.07 to 0.36, suggesting that risk factor realizations do not explain most of the time-variation of the return predictive ability of the fundamental variables. The estimates of a are all in the same direction as their respective estimates of δ_1 and the alpha ratios for all variables are very high. For instance, for asset growth Agr, investments Inv and sales growth Sgr, estimates of a are highly significant and the alpha ratios are close to 100%, implying their contributions to alphas account for almost all of their predictive ability for returns. Closer inspections of Table 3.12 reveal that these variables are in fact significantly associated with the first two factor betas, but the combination contributions to factor betas are not consistent with their associations with stock returns. Specifically, δ_1 of asset growth Agr is strongly negatively associated with the second PC factor F_2 ($b_2 = -0.025$, t-statistics$= -6.573$), which would *certeris paribus* correctly predict lower stock returns due to the positive risk premium of F_2. However, δ_1 of Agr has an unexpectedly positive association with F_1 ($b_1 = 0.012$, t-statistics$= 5.51$) which also carries a positive risk premium. The two effects cancel out, leaving almost all the return predictive ability to its contribution to alpha a. This issue is especially troubling for accruals, book-to-market and size, where their associations with factor betas would imply return predictive coefficients of the wrong sign (note that their alpha ratios are greater than 100%).[81]

There are a few fundamental variables , the associations of which with factor betas are highly consistent with their return predictive direction, while not sufficiently so to account for most of their respective return predictive ability. For example, R&D intensity RD is highly positively associated with the second PC factor, leading to positive incremental risk premium. While its positive association with the third factor implies a negative incremental premium, the small factor premium on F_3 is not large enough to offset the exposure to the

[81]Leverage is not significant in the first-step regressions, so I do not explicitly discuss it although it appears to suffer from the same issue.

risk premium of F_2.

In summary, the test results in this subsection show that the associations of many fundamental variables with factor betas do not consistently, or are not strong enough, to imply return predictive coefficients in the correct directions. Thus, all return predictive ability of firm fundamentals seems to rest in their contributions to alphas rather than betas.

Table 3.12: Second-step time-series regressions for individual firm fundamental variables

	a	$t(a)$	b_1	$t(b_1)$	b_2	$t(b_2)$	b_3	$t(b_3)$	R^2	a/δ_1
Acc	-0.156	-3.523	0.003	1.453	-0.005	-1.184	-0.063	-9.024	0.19	1.23
BM	0.367	7.667	-0.021	-8.612	0.004	0.862	-0.006	-0.780	0.23	1.22
EP	0.043	0.539	-0.001	-0.160	-0.019	-2.580	-0.125	-9.916	0.26	0.76
Opr	0.044	1.411	0.007	4.293	-0.004	-1.537	-0.028	-5.685	0.07	0.60
RD	0.303	4.298	0.001	0.346	0.051	7.992	0.112	9.952	0.32	0.83
$Cash$	0.078	1.157	0.009	2.520	0.031	5.049	0.113	10.527	0.36	0.62
Agr	-0.407	-9.776	0.012	5.508	-0.025	-6.573	-0.010	-1.571	0.17	0.99
Lev	0.096	1.597	-0.009	-2.862	-0.013	-2.373	-0.052	-5.437	0.17	1.63
Inv	-0.343	-9.295	0.007	4.034	-0.019	-5.680	0.009	1.472	0.16	0.96
$Mcap$	-0.316	-3.276	0.022	4.462	-0.002	-0.183	-0.106	-6.901	0.10	1.64
Sgr	-0.228	-6.992	0.006	3.550	-0.011	-3.640	0.039	7.507	0.30	0.93

Notes: This table reports the results of second-step time-series regressions $\hat{\delta_{1t}} = a + b_1 F_{1t+1} + b_2 F_{2t+1} + b_3 F_{3t+1} + u_t$, where F_{kt+1} with $k = 1, 2, 3$ are the the first three principal component factors extracted from the return on the 25 expected-return-sorted portfolios. Results reported include coefficient estimates, t-statistics, R^2 and the alpha ratios a/δ_1.

Test of multiple firm fundamental variables

Next, I conduct a joint test that includes all the examined firm fundamental variables in the two-step regression test simultaneously. Specifically, I first run multivariate cross-sectional regressions in the first step to obtain a time-series of multivariate predictive coefficients. In the second step, I run time-series regressions of each of predictive coefficients on the first three PC factors.

Table 3.13 Panel A reports time-series average estimates and adjusted R^2 and Fama and MacBeth (1973) t-statistics from the first-step cross-sectional regression. The signs of predictive coefficients of all variables except leverage are largely unchanged compared to the individual test. Earnings yield and cash holding, which appear insignificant in the first-step regression in individual tests, show up highly significant in the joint specification. Sales growth, on the other hand, turns insignificant at 90% level in the joint regression. The average adjusted R^2 is 3.86%, in line with existing studies (Lewellen et al. 2015; Penman and Zhu 2017).

Table 3.13 Panel B presents estimates from the second-step regressions and Panel C gives the alpha ratios calculated similarly as in individual tests.[82] As warm up, note that the first second-step regression with the first-step constant δ_0 as the regressand claims a high R^2 of almost 80%, suggesting that the time-varying means in returns are largely explained by the factor realizations, although the significant positive constant implies that the PC risk factors cannot completely drive out mispricing unrelated to the firm fundamentals considered.[83]

In contrast, like the univariate predictive coefficients, the multivariate predictive coefficients are generally poorly associated with factor realizations. Panel

[82]The only difference in the alpha ratio calculation is that the numerator δ_1 is the multivariate predictive coefficient for the respective variable.

[83]Harvey et al. (2016) argue that the conventional 't-state$>$ 2' hurdle for significance should be raised to at least 't-state$>$ 3' in asset pricing tests. In the setting of this paper, the new criterion would only strengthen my inferences.

B shows that all second-step time-series R^2s are below 30%, and the alpha ratios reported in Panel C are also similar to those reported in Table 3.12.

Accruals Acc, book-to-market BM, earnings yield EP, investment Inv and size $Mcap$ have alpha ratios above 100%, implying that their associations with the PC factor betas are inconsistent with their predictive coefficients. For example, Inv is positively associated with the first two PC components and negatively associated with the third ($b_1 = 0.001$, $b_2 = 0.012$ and $b_3 = 0.023$). The risk premiums estimated in Table 3.10 would suggest a positive predictive relation between Inv and returns if its contribution to alpha is zero, contradictory to its significant negative predictive coefficient.[84] This requires an alpha ratio that is greater than 100% to explain its average predictive coefficient.

Alpha ratios for asset growth Agr and operating profitability Opr are close to one, suggesting that their contributions to alpha explain almost all of their predictive power for returns. For Agr, the reason for this result is similar to that in the individual test: the associated incremental risk premiums to the first two factors offset each other. For Opr, the reason is that the variable is not significantly associated with the first two factor betas. Its negative association with the third PC factor beta is consistent with its positive relation with returns, but the low risk premium of the third factor is not sufficient to explain anything more than a small fraction of the predictive coefficient. The other variables, including RD, $Cash$ and Sgr, are consistently correlated with the factor betas at a more economically significant level, but all these associations explain less than 25% of their return predictive coefficients (i.e. they all have alpha ratios above 75%).

Taken together, the results again suggest that the multivariate predictive relations between firm fundamentals and stock returns are more likely to be

[84] The counter-factual predictive coefficient can be roughly calculated as $2.13 \times 0.012 - 0.146 \times 0.023 = 0.022$ (omitting the first PC factor premium because b_1 for Inv is insignificant).

driven by mispricing instead of covariance risks.

3.5 Summary

This chapter addresses the question: *Can the historical relation between firm fundamentals and stock returns be used to measure risk?* The answer suggested by my results is: *no*. I devise a novel two-step testing methodology to quantitatively evaluate the relative importance of the alpha- and beta-based explanations for the associations of firm fundamentals with stock returns. I find that the return predictive coefficients of most firm fundamentals examined are poorly associated with factor retaliations, implying that time-varying factor betas cannot explain the associations of these firm fundamentals with stock returns . The contributions to alphas of many firm fundamentals account for almost all of their return predictive ability. Hence, the predictive ability of firm fundamentals for realized returns are more likely to be attributed to mispricing rather than risks.

Table 3.13: Test of multivariate associations of firm fundamentals with risk factor betas

Panel A: First-step cross-section regression

δ_0	Acc	BM	EP	RD	$Cash$	Agr	Lev	Inv	$Mcap$	Sgr	Opr	Adj R^2
1.020	-0.096	0.193	0.301	0.297	0.150	-0.251	-0.034	-0.119	-0.180	-0.045	0.133	3.86%
(3.400)	(-2.629)	(3.450)	(4.513)	(4.920)	(2.572)	(-5.426)	(-0.263)	(-2.833)	(-1.797)	(-1.173)	(4.156)	

Panel B: Second-step time-section regressions

	Cons	b_1	b_2	b_3	R^2		Cons	b_1	b_2	b_3	R^2
δ_0	0.333	0.198	0.005	0.167	79.83%	$\delta 1(Agr)$	-0.237	0.008	-0.024	-0.007	11.54%
	2.348	27.740	0.407	7.386			-5.181	3.595	-5.739	-0.978	
$\delta 1(Acc)$	-0.119	0.003	0.005	-0.011	1.28%	$\delta 1(Lev)$	-0.042	0.014	-0.026	-0.019	2.26%
	-3.125	1.320	1.330	-1.771			-0.314	2.023	-2.093	-0.892	
$\delta 1(BM)$	0.224	-0.012	0.001	-0.033	17.05%	$\delta 1(Inv)$	-0.138	0.001	0.012	0.023	6.28%
	4.161	-4.462	0.135	-3.853			-3.220	0.638	3.000	3.401	

$\delta1(EP)$	0.323	-0.006	-0.011	-0.057	14.86%	$\delta1(Mcap)$	-0.287	0.017	0.003	-0.084	6.35%
	4.999	-1.971	-1.925	-5.543			-2.808	3.383	0.293	-5.205	
$\delta1(RD)$	0.224	0.006	0.036	0.054	22.87%	$\delta1(Sgr)$	-0.035	0.001	-0.001	0.023	5.15%
	4.011	2.257	7.079	6.108			-0.885	0.236	-0.332	3.623	
$\delta1(Cash)$	0.115	0.003	0.027	0.076	29.37%	$\delta1(Opr)$	0.127	0.001	-0.003	-0.014	2.04%
	2.236	1.223	5.834	9.324			3.813	0.798	-0.858	-2.703	

Panel C: Alpha ratios a/δ_1

	Acc	BM	EP	RD	$Cash$	Agr	Lev	Inv	$Mcap$	Sgr	Opr
	1.249	1.161	1.073	0.754	0.767	0.944	1.235	1.160	1.594	0.778	0.955

Notes: Panel A of this table reports the results of the first-step cross-sectional regressions of firm-level one-month-ahead excess returns on firm fundamental variables simultaneously. The reported estimates are time-series average estimates across the respective 416 monthly cross-sectional estimates. t-statistics reported in the parentheses are corresponding Fama and MacBeth (1973) t-statistics Newey and West (1987) adjustments. The reported Adj. R^2 is the time-series average adjusted R-squared of the respective 416 monthly cross-sectional regressions. Panel B reports the results of the second-step time-series regressions of the return predictive coefficients of each of the firm fundamentals on the forward realizations of the first three PC factors. Panel C presents the alpha ratios for each of the firm fundamental variables.

Chapter 4

Conclusion

My thesis examines the connection between firm fundamentals and the cross-section of risk and expected returns. I address two distinct but related research questions in Chapters 2 and 3 respectively.

Chapter 2 proposes a new method to construct a measure of *ex ante* expected returns for a cross-section of firms. The construction follows a theory-based forward-looking approach that accommodates stochastic risk premiums and avoids explicit assumptions about dividend policies and terminal valuation. This is achieved by explicitly estimating 'other information' that summarizes the valuation implications of the expected net present values of business activities that are not captured by the current accounting data. This 'other information' term is implied by the forward earnings expectations. The new measure of expected return exhibits consistent associations with a wide range of firm characteristics that plausibly capture firm-specific risks, and it can significantly predict future realized stock returns out-of-sample even after controlling for pre-determined firm characteristics and contemporaneous cash flow news and discount rate news.

Chapter 3 presents a new test of whether the firm-level return predictive ability of a range of firm fundamentals is attributed to differences in risk exposures ('betas') or mispricing ('alphas'). The testing methodology involves two innovations from traditional tests. First, I identify common risk factors using principal component analysis (PCA) for portfolios of stock ranked by signals of expected returns. This approach guarantees that the risk factors are systematic and economically significant, and it bypasses the controversy over the economic identify of true risk factors. Second,I estimate the contributions of firm fundamentals in determining both alphas and betas in a two-step estimation procedure. This procedure tests risk-based and mispricing-based explanations on equal footing, thus being more powerful than traditional 'beta-only' tests. The results suggest that, while some firm fundamental variables are modestly associated with firms' betas, the return predictive ability of many firm fundamentals at the firm level is mostly attributed to their contributions to alphas. Hence, the cross-sectional difference in firm-specific risk exposures do not capture the roles of firm fundamentals in predicting stock returns.

Appendix A

Appendix to Chapter 2

Proof of Proposiion 1

Proof.

$$
\begin{aligned}
P_t &= \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} d_{t+j}] \\
&= \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (x_{t+j} - (x_{t+j} - d_{t+j}))] \\
&= \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} x_{t+j}] - \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (x_{t+j} - d_{t+j})] \\
&= \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (x_{t+1} + \sum_{k=2}^{j} \Delta x_{t+k})] - \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (x_{t+j} - d_{t+j})]
\end{aligned}
$$

where $\Delta x_{t+k} = x_{t+k} - x_{t+k-1}$. The expectations inside the summation of the second term subtracted in the above equation can be re-written as

$$
\begin{aligned}
&\mathbb{E}_t[\frac{m_{t+j}}{m_t}(x_{t+j}-d_{t+j})] \\
&= \mathbb{E}_t[(\frac{m_{t+j}-m_{t+j+1}}{m_t}+\frac{m_{t+j+1}-m_{t+j+2}}{m_t}+\frac{m_{t+j+2}-m_{t+j+3}}{m_t}+\cdots)(x_{t+j}-d_{t+j})] \\
&= \sum_{k=1}^{\infty}\mathbb{E}_t[\frac{m_{t+j+k}-m_{t+j+k+1}}{m_t}(x_{t+j}-d_{t+j})] \\
&= \sum_{k=1}^{\infty}\mathbb{E}_t[\frac{1}{m_t}(m_{t+j+k}-m_{t+j+k+1})(x_{t+j}-d_{t+j})] \\
&= \sum_{k=1}^{\infty}\mathbb{E}_t[\frac{1}{m_t}m_{t+j+k+1}(\frac{m_{t+j+k}}{m_{t+j+k+1}}-1)(x_{t+j}-d_{t+j})] \\
&= \sum_{k=1}^{\infty}\mathbb{E}_t[\frac{1}{m_t}\,\mathbb{E}_{t+j+k}[m_{t+j+k+1}(\frac{m_{t+j+k}}{\mathbb{E}_{t+j+k}[m_{t+j+k+1}]}-1)](x_{t+j}-d_{t+j})] \\
&= \sum_{k=1}^{\infty}\mathbb{E}_t[\frac{m_{t+j+k+1}}{m_t}(R^f_{t+j+k}-1)(x_{t+j}-d_{t+j})]
\end{aligned}
$$

where the last equality follows from the definition of the risk-free rate and the law of iterated expectation. Now substitute the above equation back to the former, one gets the following

$$
\begin{aligned}
P_t &= \sum_{j=1}^{\infty}\mathbb{E}_t[\frac{m_{t+j}}{m_t}(x_{t+1}+\sum_{k=2}^{j}\Delta x_{t+k})]-\sum_{s=1}^{\infty}\mathbb{E}_t[\frac{m_{t+j+s+1}}{m_t}(R^f_{t+j+s}-1)(x_{t+j}-d_{t+j})] \\
&= \sum_{j=1}^{\infty}\mathbb{E}_t[\frac{m_{t+j}}{m_t}x_{t+1}]+\sum_{j=2}^{\infty}\sum_{s=j}^{\infty}\mathbb{E}_t[\frac{m_{t+s}}{m_t}(\Delta x_{t+j}-(R^f_{t+s-1}-1)(x_{t+j-1}-d_{t+j-1}))]
\end{aligned}
$$

as claimed. □

Proof of Proposition 2

Proof.

$$
\begin{aligned}
P_t &= \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} d_{t+j}] \\
&= \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (b_{t+j-1} + x_{t+j} - b_{t+j})] \\
&= b_t - \frac{m_t}{m_t} b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (b_{t+j-1} + x_{t+j} - b_{t+j})] \\
&= b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (b_{t+j-1} + x_{t+j})] - \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} b_{t+j}] - \frac{m_t}{m_t} b_t \\
&= b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (b_{t+j-1} + x_{t+j})] - \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j-1}}{m_t} b_{t+j-1}] \\
&= b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (b_{t+j-1} + x_{t+j})] - \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j-1}}{\mathbb{E}_{t+j-1}[m_{t+j}]} \frac{\mathbb{E}_{t+j-1}[m_{t+j}]}{m_t} b_{t+j-1}] \\
&= b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (b_{t+j-1} + x_{t+j})] - \sum_{j=1}^{\infty} \mathbb{E}_t[R^f_{t+j-1} \frac{\mathbb{E}_{t+j-1}[m_{t+j}]}{m_t} b_{t+j-1}] \\
&= b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (b_{t+j-1} + x_{t+j})] - \sum_{j=1}^{\infty} \mathbb{E}_t[R^f_{t+j-1} \frac{m_{t+j}}{m_t} b_{t+j-1}] \\
&= b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} (x_{t+j} - (R^f_{t+j-1} - 1) b_{t+j-1})] \\
&= b_t + \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} x^a_{t+j}]
\end{aligned}
$$

□

In the proof, the second equality follows from the clean surplus relation (Assumption 3), the seventh equality follows by the defition of the risk-free rate, and the eighth applies the law of iterated expectation.

Proof of Proposition 3

The following version of Stein's Lemma that characterizes a property of the normal distribution is invoked in the proof.

Lemma 1 (**Stein's Lemma**). *A random variable* $y \sim N(0, \sigma^2)$ *if and only if*

$$\mathbb{E}[yf(y)] = \sigma^2\, \mathbb{E}[f'(y)]$$

for any absolutely continuous function $f(\cdot)$ *such that* $\mathbb{E}[|f'(y)|] < \infty$.

Proof. I start by defining market goodwill as

$$g_t := P_t - b_t$$

This definition implies, through the law of iterated expectations, the following recursive formula:

$$\begin{aligned} g_t &= \sum_{j=1}^{\infty} \mathbb{E}_t[\frac{m_{t+j}}{m_t} x^a_{t+j}] = \mathbb{E}_t\{\frac{m_{t+1}}{m_t}(x^a_{t+1} + \sum_{j=2}^{\infty} \mathbb{E}_{t+1}[\frac{m_{t+j}}{m_t} x^a_{t+j}])\} \\ &= \mathbb{E}_t[\frac{m_{t+1}}{m_t}(x^a_{t+1} + g_{t+1})] \end{aligned} \tag{A.1}$$

Conjecture a linear pricing rule

$$g_t = \mathbf{b}_t' X_t = \alpha_t x^a_t + \beta_t v_t$$

where $\mathbf{b}_t$ is independent of X_t. Substitute this conjecture into equation (A.1), then one obtains

$$
\begin{aligned}
\mathbf{b}_t' X_t &= \mathbb{E}_t[k \exp\{-\rho z_{t+1}\}(x^a_{t+1} + g_{t+1})] \\
&= \mathbb{E}_t[k \exp\{-\rho z_{t+1}\}(\mathbf{b}_{t+1} + \mathbf{e}_1)' X_{t+1}] \\
&= \mathbb{E}_t[k \exp\{-\rho z_{t+1}\}](\mathbb{E}_t[\mathbf{b}_{t+1}] + \mathbf{e}_1)' \, \mathbb{E}_t[X_{t+1}] \\
&+ COV_t[k \exp\{-\rho z_{t+1}\}, (\mathbf{b}_{t+1} + \mathbf{e}_1)' X_{t+1}] \\
&= \frac{1}{R^f_t}(\mathbb{E}_t[\mathbf{b}_{t+1}] + \mathbf{e}_1)' \Phi^{(t)} X_t \\
&+ COV_t[k \exp\{-\rho z_{t+1}\}, (\mathbf{b}_{t+1} + \mathbf{e}_1)' X_{t+1}] \qquad \text{(A.2)}
\end{aligned}
$$

where $\mathbf{e}_1$ is the first basis vector of $\mathbb{R}^2$. By Assumption 6, the covariance term in equation (A.2) can be simplified to

$$
\begin{aligned}
& COV_t[k \exp\{-\rho z_{t+1}\}, (\mathbf{b}_{t+1} + \mathbf{e}_1)' X_{t+1}] \\
=& k COV_t[\exp\{-\rho \gamma' \epsilon_{t+1} - \frac{1}{2}\rho^2 \gamma' \Sigma_t \gamma + \eta_{t+1}\}, (\mathbf{b}_{t+1} + \mathbf{e}_1)' \epsilon_{t+1}] \\
=& k \, \mathbb{E}_t[\exp\{-\rho \gamma' \epsilon_{t+1} - \frac{1}{2}\rho^2 \gamma' \Sigma_t \gamma + \eta_{t+1}\}(\mathbf{b}_{t+1} + \mathbf{e}_1)' \epsilon_{t+1}] \qquad \text{(A.3)}
\end{aligned}
$$

where the last equality follows from Lemma 1. Because Σ_t is a constant at date t and η_{t+1} is independent of ϵ_{t+1}, equation (A.3) can be further reduced to

$$
\frac{1}{R^f_t} \exp\{-\frac{1}{2}\rho^2 \gamma' \Sigma_t \gamma\} \, \mathbb{E}_t[\exp\{-\rho \gamma' \epsilon_{t+1}\}(\mathbf{b}_{t+1} + \mathbf{e}_1)' \epsilon_{t+1}] \qquad \text{(A.4)}
$$

Note that the following is true by Stein's Lemma because $\gamma' \epsilon_{t+1} \sim N(0, \gamma' \Sigma_t \gamma)$

$$
\begin{aligned}
-\rho\gamma' \, \mathbb{E}_t[\exp\{-\rho\gamma'\epsilon_{t+1}\}\epsilon_{t+1}] &= \mathbb{E}_t[\exp\{-\rho\gamma'\epsilon_{t+1}\}(-\rho\gamma'\epsilon_{t+1})] \\
&= \rho^2\gamma'\Sigma_t\gamma \exp\{\frac{1}{2}\rho^2\gamma'\Sigma_t\gamma\}
\end{aligned}
$$

But this further implies

$$
\begin{aligned}
&\mathbb{E}_t[\exp\{-\rho\gamma'\epsilon_{t+1}\}\epsilon_{t+1}] = -\rho\Sigma_t\gamma \exp\{\frac{1}{2}\rho^2\gamma'\Sigma_t\gamma\} \\
\Rightarrow &\mathbb{E}_t[\exp\{-\rho\gamma'\epsilon_{t+1}\}(\mathbf{b}_{t+1} + \mathbf{e}_1)'\epsilon_{t+1}] = -\rho(\mathbb{E}_t[\mathbf{b}_{t+1}] + \mathbf{e}_1)'\Sigma_t\gamma \exp\{\frac{1}{2}\rho^2\gamma'\Sigma_t\gamma\}
\end{aligned}
$$

Collecting the above results, one obtains

$$
\mathbf{b}_t'X_t = \frac{1}{R_t^f}(\mathbb{E}_t[\mathbf{b}_{t+1}] + \mathbf{e}_1)'(\Phi^{(t)}X_t - \rho\Sigma_t\gamma) \tag{A.5}
$$

That is, the goodwill is the present value of risk-adjusted expected future firm fundamentals. It is increasing in expected future abnormal earnings $\Phi^{(t)}X_t$, decreasing in risk aversion ρ and risk exposure, which is the product of firm-specific volatility Σ_t and the co-movement of firm-level shocks with aggregate consumption growth γ.

Further note that $\Sigma_t = \mathbf{D} \otimes X_t$, so

$$
\begin{aligned}
\Sigma_t\gamma &= \mathbf{D}^*X_t \\
\text{where} \quad \mathbf{D}^* &= [\mathbf{D}_1 \ \ \mathbf{D}_2]\gamma
\end{aligned}
$$

Hence, substituting this into equation (A.5) yields

$$\mathbf{b}_t' X_t = \frac{1}{R_t^f}(\mathbb{E}_t[\mathbf{b}_{t+1}] + \mathbf{e}_1)'(\Phi^{(t)} - \rho \mathbf{D}^*) X_t$$

$$\Rightarrow \mathbf{b}_t = \frac{1}{R_t^f}(\Phi^{(t)} - \rho \mathbf{D}^*)'(\mathbb{E}_t[\mathbf{b}_{t+1}] + \mathbf{e}_1) \tag{A.6}$$

Apply recursive substitution to equation (A.6), and one gets

$$\mathbf{b}_t = \sum_{j=1}^{\infty} \{\Pi_{k=0}^{j-1} \mathbb{E}_t[\frac{1}{R_{t+k}^f}]\}[(\Phi^{(t)} - \rho \mathbf{D}^*)']^j \mathbf{e}_1 \tag{A.7}$$

Note $\mathbf{b}_t$ is known at date t and is independent of X_t as conjectured. Let α_t denote the first element of $\mathbf{b}_t$ (b_{t1}), and rewrite the product of v_t with the second element of $\mathbf{b}_t$ as $\vartheta_t = b_{t2} v_t$. This concludes the proof of Proposition 3. □

Proof of Claim 1

Proof.

$$\mathbb{E}_t[\vartheta_{t+1}] = \mathbb{E}_t[\beta_{t+1} v_{t+1}] = \mathbb{E}_t[\beta_{t+1}]\phi^{(t)} v_t = \frac{\mathbb{E}_t[\beta_{t+1}]\phi^{(t)}}{\beta_t}\vartheta_t$$

Now Claim 1 becomes apparent. □

Appendix B

Appendix to Chapter 3

Derivation of equation (3.3) from equation (3.2)

First substitute $\alpha_{it+1} = \bar{\alpha} + a'X_{it} + \epsilon^{\alpha}_{it+1}$ and $\beta^k_{it+1} = \bar{\beta}^k + b^{k\prime}X_{it} + \epsilon^k_{it+1}$ into $R_{it+1} = \alpha_{it+1} + \sum_{j=1}^{K} \beta^k_{it+1} f^k_{t+1} + \epsilon_{it+1}$:

$$
\begin{aligned}
R_{it+1} &= \bar{\alpha} + a'X_{it} + \epsilon^{\alpha}_{it+1} + \sum_{j=1}^{K} (\bar{\beta}^k + b^{k\prime}X_{it} + \epsilon^k_{it+1}) f^k_{t+1} + \epsilon_{it+1} \\
&= \bar{\alpha} + a'X_{it} + \sum_{j=1}^{K} \bar{\beta}^k f^k_{t+1} + \sum_{j=1}^{K} b^{k\prime} X_{it} f^k_{t+1} + (\epsilon_{it+1} + \epsilon^{\alpha}_{it+1} + \sum_{j=1}^{K} \epsilon^k_{it+1} f^k_{t+1}) \\
&= \bar{\alpha} + a'X_{it} + \sum_{j=1}^{K} \bar{\beta}^k f^k_{t+1} + \sum_{j=1}^{K} b^{k\prime} X_{it} f^k_{t+1} + \varepsilon_{it+1}
\end{aligned}
$$

The last equality defines ε_{it+1}. Now take conditional expectations on both sides of the equation, giving

$$
\mathbb{E}_t[R_{it+1}] = \bar{\alpha} + a'X_{it} + \sum_{j=1}^{K} \bar{\beta}^k \gamma^k_t + \sum_{j=1}^{K} b^{k\prime} X_{it} \gamma^k_t
$$

which implies equation (3.3).

Derivation of equation (3.5)

From equation (3.3)

$$\delta_{1t} = a + \sum_{j=1}^{K} b^{k\prime}\, \mathbb{E}_t[f_{kt+1}]$$

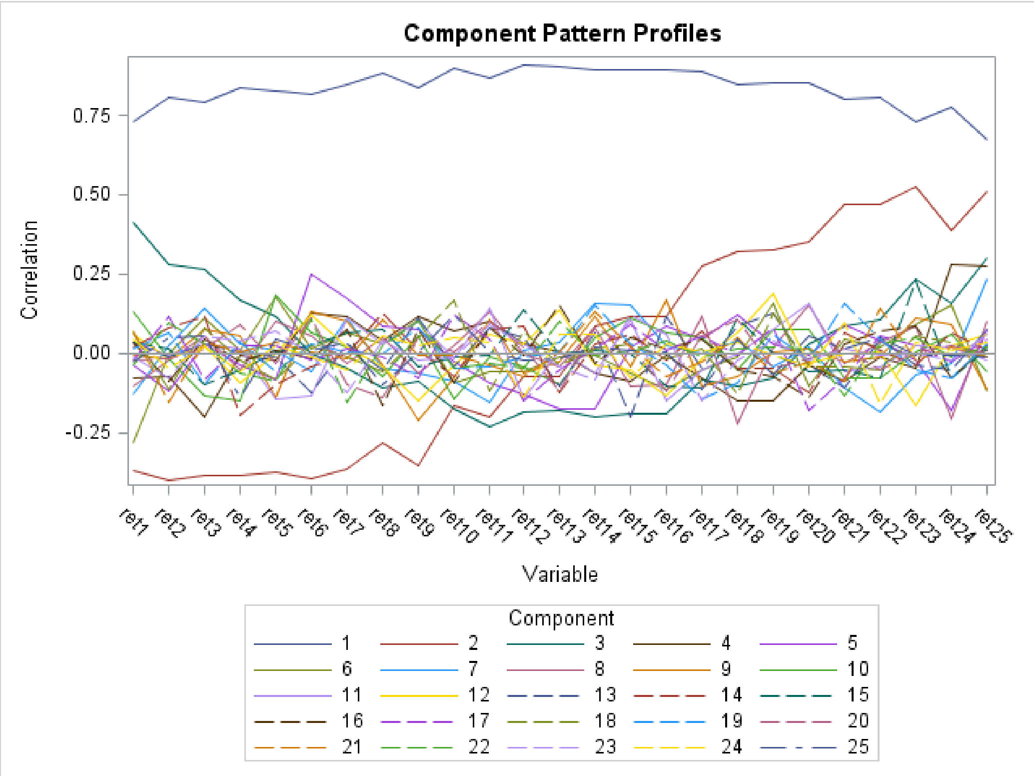
By the defining property of conditional expectations $f_{kt+1} = \mathbb{E}_t[f_{kt+1}] + u^k_{t+1}$, where u^k_{t+1} is the zero-mean expectation error. This implies

$$\delta_{1t} = a + \sum_{j=1}^{K} b^k f_{kt+1} - \sum_{j=1}^{K} b^k u^k_{t+1}$$

Define $u_{1t} = -\sum_{j=1}^{K} b^k u^k_{t+1} + (\hat{\delta_{1t}} - \delta_{1t})$, which is of zero-mean. Apply similar reasoning to u_{0t} and this suffices for the purpose.

Additional tables and figures

Figure B.1: All principal component factor portfolio weights



Notes: Panel A and Panel B report descriptive statistics for the estimation sample and testing sample respectively. Sample means, standard deviations, 1th, 25th, 50th, 75th and 99th percentiles are reported in columns 2-8 respectively. b_t/P_t is the book-to-price ratio. x_t/P_t and $FE_{t,t+1}/P_t$ are trailing and forward earnings yields respectively. b_{t-1}/P_t is the ratio of lagged book value per share over current stock price. Lev_t is financial leverage; $Mcap_t$ is the natural log of market capitalization; Acc_t is operating accruals; $Beta_t$ is CAPM beta; ΔNOA_t is net operating asset growth; $Saleg_t$ is realized (percentage) sales growth rate; Inv_t is firm investments in property, plant & equipment and inventory; Exf_t is total external financing; Mom_t is momentum (past 12-month buy-and-hold return); and $R_{t,t+1}$ is one-period-ahead realized return.

Table B.1: Principal component weights (raw weights scaled up by a factor of 10)

	Principal components												
Portfolio	1	2	3	4	5	6	7	8	9	10	11	12	13
1 (Low)	1.83	-2.24	5.20	-4.21	5.87	-0.90	-2.00	0.36	-1.08	0.10	0.20	0.25	0.82
2	1.93	-2.43	3.17	-0.31	-1.58	2.15	3.75	3.09	-0.86	-4.61	0.34	1.42	-1.60
3	1.95	-2.50	2.15	0.05	-2.92	0.93	0.55	-1.80	3.22	-0.27	-3.78	-0.84	4.08
4	1.99	-2.16	1.58	-1.05	-1.76	-2.03	2.23	-3.83	2.20	3.78	3.64	0.96	-0.63
5	2.01	-2.16	0.80	0.99	-0.97	-0.38	-1.15	-0.51	-2.11	1.77	-1.17	-2.76	-3.61
6	2.01	-2.07	0.31	1.95	-1.81	0.21	0.04	1.32	-1.50	3.27	0.73	-0.10	2.25
7	2.05	-1.63	-0.10	1.97	-0.93	0.51	-0.71	-1.55	-0.48	-1.05	-0.99	0.17	-4.23
8	2.06	-1.56	-0.78	1.76	-0.47	-0.76	-2.09	-1.19	-1.19	0.37	-1.57	1.78	-0.56
9	2.04	-1.60	-1.21	1.66	-0.38	1.41	-0.31	4.95	-2.12	1.20	3.06	-2.20	2.02
10	2.08	-1.13	-1.27	1.37	1.11	0.30	-1.73	0.35	1.29	-2.66	1.12	1.22	-0.61
11	2.07	-1.01	-1.88	1.31	0.49	-1.38	-2.28	-0.63	2.05	-1.24	1.67	-0.38	2.74
12	2.09	-0.48	-2.00	0.32	1.45	-1.10	-1.16	-0.47	1.56	-1.53	-1.73	3.02	-0.25
13	2.08	-0.31	-2.35	-0.05	2.66	0.09	-2.01	1.35	-0.03	2.39	-3.22	-0.05	-0.17
14	2.09	-0.26	-2.19	0.23	1.20	-1.27	0.88	-0.67	-0.72	-1.86	1.94	-1.07	-1.94
15	2.08	0.51	-2.11	-0.38	2.75	0.16	3.23	-2.52	0.44	-1.85	2.13	-4.45	1.03
16	2.09	0.65	-1.56	-0.87	0.43	1.06	3.21	0.43	2.09	-0.71	-2.83	0.99	-0.59
17	2.08	0.99	-1.37	-1.50	-0.01	1.16	0.93	-1.85	-1.86	-0.66	0.39	0.19	2.92
18	2.06	1.24	-1.17	-2.35	-0.18	2.09	0.34	3.54	3.30	2.44	0.89	1.72	-0.88
19	2.03	1.68	-1.50	-2.12	0.33	-0.62	3.04	0.66	-1.23	3.12	-0.67	2.22	-0.90
20	2.01	2.04	-0.34	-1.99	-1.99	0.89	-0.59	-1.21	-4.81	-1.20	-2.44	-0.23	2.58
21	1.97	2.51	0.69	-2.51	-1.63	0.95	-1.27	-0.77	-0.02	0.70	-0.79	-3.93	-3.00
22	1.95	2.66	0.62	-1.23	-2.61	-0.84	-2.56	-1.09	-1.70	-1.37	3.58	4.03	-0.04
23	1.85	3.32	2.08	-0.13	-1.31	1.96	-3.42	0.94	3.77	-0.80	0.94	-2.22	-0.13
24	1.85	3.06	2.09	1.85	-0.65	-7.64	1.58	2.95	0.39	-0.80	-1.48	-1.14	0.57
25 (High)	1.66	3.87	3.38	5.87	3.23	3.16	1.52	-1.81	-0.60	1.65	0.09	1.43	0.29

Portfolio	Principal components											
	14	15	16	17	18	19	20	21	22	23	24	25
1 (Low)	0.60	-1.40	-0.70	-0.39	-0.82	-0.69	-0.33	-0.29	0.90	-0.27	0.42	-0.38
2	-1.92	1.97	2.17	-0.47	1.80	0.56	1.18	-0.99	-1.96	-0.29	0.64	0.15
3	1.81	0.54	1.05	2.12	0.10	2.06	-2.08	-0.07	3.48	0.55	-0.18	0.29
4	-0.88	1.03	-2.55	0.48	1.01	0.09	2.47	0.06	-1.99	1.69	-0.18	2.16
5	1.75	2.11	-0.52	-0.52	2.50	0.15	-1.13	4.22	-0.61	-1.93	-2.33	-3.80
6	-4.39	-2.80	2.48	-2.57	-2.83	-1.93	-2.22	1.66	-0.50	1.14	1.39	-1.22
7	1.11	-5.73	-0.57	3.12	-2.43	1.17	1.18	-1.02	-0.58	-2.20	2.30	0.86
8	-0.16	3.59	-0.54	-3.47	-1.81	-2.01	0.06	-4.25	1.50	-3.72	-1.26	2.69
9	3.49	0.28	-1.70	2.41	0.53	-1.87	1.98	-0.43	1.95	1.04	-0.04	2.09
10	0.23	-1.71	-0.46	-1.16	-1.09	1.98	-1.90	0.23	-1.41	3.89	-6.54	1.19
11	1.90	-1.41	0.95	-2.56	3.82	0.92	1.01	-2.96	-2.51	-0.54	2.54	-3.77
12	2.07	2.30	2.54	0.14	-1.84	-2.50	2.75	4.91	-0.53	2.10	2.61	0.80
13	-4.61	1.12	0.70	4.05	3.52	1.41	-0.24	-1.03	-1.56	0.41	0.28	1.85
14	-2.65	1.84	-2.01	-0.74	-1.01	3.22	-0.31	-0.14	5.54	2.27	2.69	-2.07
15	0.07	-0.08	2.16	-0.15	0.01	-0.94	-2.68	1.53	-0.96	-3.19	0.03	3.35
16	-0.61	-2.27	-4.45	-0.78	2.04	-5.49	-1.10	-0.35	0.99	0.50	-0.48	-1.70
17	-1.20	1.28	-0.01	3.47	-3.62	-0.41	3.01	-1.05	-1.38	-1.46	-2.94	-4.59
18	1.71	1.68	-1.71	-0.55	-2.94	2.94	-3.06	0.26	-2.17	-2.32	1.65	-0.67
19	1.81	-2.59	4.18	-1.96	1.76	2.05	2.30	-0.41	3.05	-0.61	-2.22	0.17
20	0.47	-0.77	-3.44	-2.65	0.67	2.53	0.58	1.76	-2.11	1.03	1.56	2.45
21	1.33	1.08	2.62	-0.22	-1.22	-2.15	-0.72	-3.63	-1.11	4.48	0.84	-0.22
22	-0.06	-0.12	1.01	2.92	2.42	-1.85	-3.96	0.58	1.51	-0.93	0.29	0.09
23	-2.96	-0.91	-0.22	-1.50	0.46	-0.14	3.92	2.10	1.90	-2.23	-1.11	0.86
24	0.08	0.01	-0.64	0.96	-1.26	0.34	-0.24	-0.31	-1.07	-0.45	-0.57	0.04
25 (High)	1.05	1.02	-0.24	0.02	0.43	0.63	-0.42	-0.39	-0.23	1.11	0.71	-0.55

Table B.2: Time-series regressions of 25 expected-return-sorted portfolio returns on Fama-French factors

Portfolio	α	$t(\alpha)$	R_m^e	$t(R_m^e)$	SMB	$t(SMB)$	HML	$t(HML)$	R^2	$\bar{R}^2$	$\|\alpha\|$
1 (Low)	-2.18	-7.01	1.41	18.53	0.53	4.69	0.05	0.40	0.526	0.523	2.181
2	-1.12	-4.97	1.36	24.57	0.34	4.16	0.10	1.10	0.644	0.642	1.125
3	-0.89	-4.01	1.24	22.87	0.34	4.20	0.29	3.28	0.601	0.598	0.885
4	-0.53	-2.83	1.23	26.92	0.17	2.55	0.10	1.33	0.674	0.672	0.530
5	-0.18	-1.01	1.15	25.83	0.15	2.35	0.08	1.14	0.656	0.653	0.183
6	-0.17	-0.87	1.10	23.80	0.16	2.28	0.02	0.27	0.624	0.621	0.165
7	-0.22	-1.45	1.09	28.98	0.12	2.09	0.16	2.62	0.698	0.696	0.223
8	-0.06	-0.41	1.09	33.33	0.07	1.46	0.19	3.59	0.750	0.748	0.055
9	-0.04	-0.28	1.00	25.81	0.09	1.51	0.07	1.13	0.652	0.649	0.045
10	-0.11	-0.89	1.09	35.77	0.01	0.14	0.07	1.36	0.778	0.777	0.111
11	-0.12	-0.94	0.99	32.38	-0.04	-0.88	0.18	3.70	0.732	0.730	0.117
12	-0.06	-0.49	1.02	37.00	0.01	0.27	0.04	0.89	0.792	0.790	0.055
13	0.04	0.34	0.94	35.46	0.02	0.49	0.08	1.83	0.775	0.773	0.037
14	0.06	0.53	0.96	35.43	0.07	1.70	0.05	1.10	0.779	0.778	0.059
15	-0.08	-0.72	0.97	34.62	0.18	4.44	0.08	1.67	0.778	0.776	0.082
16	0.26	2.15	0.93	31.45	0.13	2.88	-0.04	-0.81	0.747	0.745	0.258
17	0.30	2.52	0.92	31.09	0.33	7.45	0.09	1.90	0.751	0.750	0.305
18	0.36	2.42	0.91	25.20	0.31	5.87	-0.06	-1.01	0.678	0.676	0.357
19	0.07	0.51	0.91	26.67	0.39	7.79	0.06	1.13	0.701	0.699	0.071
20	0.34	2.37	0.94	26.88	0.34	6.57	-0.07	-1.15	0.708	0.706	0.339
21	0.41	2.42	0.88	21.33	0.57	9.43	-0.14	-2.07	0.652	0.649	0.407
22	0.51	3.05	0.91	22.25	0.50	8.22	-0.02	-0.23	0.643	0.640	0.511
23	0.59	2.90	0.89	17.86	0.67	9.10	-0.14	-1.76	0.583	0.579	0.588
24	0.45	2.43	0.99	21.70	0.45	6.69	-0.01	-0.13	0.618	0.616	0.454
25 (High)	0.92	3.27	1.06	15.31	0.98	9.67	-0.25	-2.25	0.543	0.540	0.920
Average									**0.683**	**0.681**	**0.402**

Table B.3: Time-series regressions of 25 expected-return-sorted portfolio returns on Fama-French-Carhart factors

Portfolio	α	$t(\alpha)$	R_m^e	$t(R_m^e)$	SMB	$t(SMB)$	HML	$t(HML)$	UMD	$t(UMD)$	R^2	$\bar{R}^2$	$\lvert\alpha\rvert$
1 (Low)	-1.24	-4.87	1.23	19.99	0.48	5.44	-0.32	-3.18	-0.98	-15.58	0.703	0.700	1.235
2	-0.50	-2.57	1.24	26.41	0.31	4.59	-0.15	-1.90	-0.65	-13.49	0.754	0.752	0.499
3	-0.30	-1.55	1.12	24.10	0.31	4.58	0.06	0.75	-0.61	-12.77	0.715	0.712	0.298
4	-0.01	-0.09	1.13	29.13	0.15	2.64	-0.10	-1.61	-0.53	-13.41	0.774	0.772	0.014
5	0.28	1.78	1.06	27.27	0.13	2.37	-0.10	-1.59	-0.48	-12.21	0.748	0.746	0.284
6	0.41	2.62	0.99	26.42	0.13	2.40	-0.20	-3.31	-0.59	-15.41	0.762	0.760	0.406
7	0.18	1.35	1.01	31.08	0.10	2.07	0.00	0.04	-0.42	-12.58	0.783	0.781	0.181
8	0.24	1.93	1.03	34.54	0.06	1.32	0.07	1.54	-0.30	-9.94	0.799	0.797	0.238
9	0.34	2.36	0.92	26.80	0.07	1.38	-0.08	-1.38	-0.39	-11.20	0.734	0.731	0.336
10	0.06	0.49	1.06	35.39	0.00	-0.03	0.00	0.00	-0.18	-5.83	0.796	0.794	0.060
11	0.03	0.26	0.96	31.76	-0.05	-1.05	0.12	2.51	-0.16	-5.05	0.748	0.746	0.033
12	-0.03	-0.30	1.02	36.16	0.01	0.25	0.03	0.69	-0.02	-0.75	0.792	0.790	0.035
13	0.07	0.66	0.93	34.59	0.02	0.45	0.06	1.46	-0.04	-1.38	0.776	0.774	0.073
14	-0.03	-0.29	0.97	35.88	0.07	1.83	0.08	1.89	0.09	3.41	0.786	0.783	0.033
15	-0.21	-1.78	1.00	35.63	0.19	4.68	0.12	2.72	0.13	4.49	0.788	0.786	0.206
16	0.19	1.56	0.94	31.45	0.13	2.96	-0.01	-0.27	0.07	2.24	0.750	0.748	0.192
17	0.10	0.88	0.96	33.71	0.33	8.11	0.17	3.65	0.21	7.17	0.779	0.777	0.103
18	0.08	0.55	0.96	28.31	0.32	6.59	0.05	0.90	0.29	8.32	0.725	0.722	0.078
19	-0.22	-1.72	0.97	30.68	0.41	8.88	0.18	3.44	0.30	9.46	0.755	0.752	0.223
20	0.04	0.31	1.00	30.76	0.35	7.50	0.05	0.95	0.31	9.26	0.759	0.756	0.042
21	0.01	0.09	0.96	25.74	0.59	10.99	0.02	0.26	0.41	10.75	0.729	0.726	0.014
22	0.08	0.57	1.00	27.69	0.52	9.92	0.15	2.57	0.44	12.02	0.736	0.734	0.085
23	0.08	0.43	0.99	22.56	0.69	10.90	0.06	0.81	0.53	11.85	0.690	0.687	0.078
24	0.01	0.04	1.08	26.42	0.47	7.97	0.16	2.48	0.46	11.12	0.707	0.705	0.006
25 (High)	0.25	0.99	1.19	19.17	1.01	11.32	0.01	0.10	0.69	10.95	0.647	0.643	0.252
Average											**0.749**	**0.747**	**0.200**

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