441

ROY VERBEEK - Essays on Empirical Asset Pricing

ERIM

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Essays on Empirical Asset Pricing

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Essays over het empirisch prijzen van financiële producten

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Roy Verbeek

Rotterdam, August 2017

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Chapter 1

Introduction

This thesis bundles three studies on empirical asset pricing. At its most basic level, the discipline of empirical asset pricing is concerned with the question of why some assets offer higher expected returns than others. The capital asset pricing model (CAPM) by Sharpe (1964), Lintner (1965a,b), and Mossin (1966) is the classical model that provides an answer to this question. In this model, an asset's expected return is determined by how much it is exposed to one fundamental risk factor: the market factor. An asset that has a large exposure to this factor is risky, because it pays off poorly when the market goes down and pays off well when the market goes up, which leads to high variation in future wealth. To get risk-averse investors to hold this asset, it needs to offer high expected returns as compensation for this undesirable feature. In contrast, an asset that has a low exposure to the market factor is less risky because it is associated with less variation in future wealth. Investors, therefore, accept a lower expected return on such an asset.

Given its intuitive nature and lacking decent alternative models, the CAPM has served as the main workhorse for quite some time. However, early studies already presented evidence questioning the empirical validity of the CAPM (e.g., Black, Jensen, and Scholes, 1972; Blume and Friend, 1973; Fama and MacBeth, 1973), which has led to a search for models that better match the empirical patterns in stock prices. Some of these alternative models, and perhaps also those that are most popular, are the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Hou, Xue, and Zhang (2015) four-factor model. In fact, scholars have proposed a plethora of factors that are related to the cross-section of expected returns (Harvey, Liu, and Zhu, 2016).

So why do some assets offer higher returns than others? There is no clear-cut answer to this fundamental asset pricing question, and we have to work with models that best fit the data. However, it is not straightforward to pick a model that best fits the empirical properties of asset returns. There are many reasons for this, such as the fact that some models might work well for certain firms or portfolios but not for others (Lewellen, Nagel, and Shanken, 2010). Moreover, estimation error in the risk loadings and risk premia can severely undermine the pricing ability of asset pricing models (e.g., Fama and French, 1997; Levi and Welch, 2014). The answer also depends on the investment horizon used to evaluate the models, since some factors might be priced at certain horizons but not at others (e.g., Kamara, Korajczyk, Lou, and Sadka, 2016).

The answer to the fundamental asset pricing question is important to several audiences, although for different reasons. Investors, for instance, might want to understand the exposures of their investments to factors that are empirically associated with a significant price of risk. They might want to use this information to compute expected returns and to form portfolios that match their risk preferences. CFOs and other managers throughout an organization might be interested in knowing why some assets are associated with higher expected returns than others for capital budgeting purposes. In particular, they need reliable asset pricing models that capture the expected risks many years into the future in order to obtain estimates of the cost of equity capital for net present value (NPV) calculations. Academic researchers are usually interested in identifying how many factors are priced and estimating the corresponding risk premia. This knowledge is used to construct models that explain why asset prices vary in the cross-section and over time. These models are subsequently used to investigate other important areas within the empirical asset pricing discipline. For instance, models are used to determine whether some investors are able to generate abnormal returns relative to risk-adjusted benchmark returns, and to decompose stock return volatility into a component that captures systematic risk and one that captures idiosyncratic risk.

The three papers that form the basis of this thesis cover rather distinct topics in the field of empirical asset pricing. Like most studies in this field, the papers are based on US data. Each paper is likely to be of interest to at least one of the previously discussed audiences for which answers to empirical asset pricing questions are important. In particular, Chapter 2 might be of special interest to investors and researchers because it investigates whether risk factors are priced, by how much, and at which investment horizon. Chapter 3 is particularly relevant for CFOs because it discusses whether and how asset pricing models should be used to compute the cost of equity capital. Researchers might be particularly interested in Chapter 4, which enriches our understanding of why stock prices vary, both in the cross-section and time series.

In the second chapter, I study the pricing of systematic risk factors across different horizons. I apply wavelet analysis to extract components of stock returns and widely used risk factors at different horizons and subsequently estimate risk loadings as well as risk premia for each of the horizons separately. I find that the market and size factors are priced at horizons up to sixteen months, while the value, momentum, liquidity, profitability, and investment factors are not priced at any horizon. My results create scope for future research because they leave two open questions. First, future research should focus on providing economic explanations for why certain risk factors are priced at certain horizons and not at others. Second, more research should be directed towards understanding which systematic risk factors are priced into individual stocks as opposed to portfolios.

In the third chapter, I examine whether and how popular asset pricing models can be used by CFOs and other mangers in a firm interested in computing the cost of equity capital. The cost of equity capital is important because it is used for NPV calculations and can therefore have a huge impact on valuation and investment decisions. The CAPM has been used for a long time, but given the evidence that the CAPM fails to explain the cross-section of stock returns, and given that many new asset pricing models have been proposed that seem to outperform the CAPM, it is no longer clear which model should be used. I consider (1) the CAPM, (2) the Fama and French (1993) three-factor model, (3) the Carhart (1997) four-factor model, (4) the Fama and French (2015) five-factor model, and (5) the Hou, Xue, and Zhang (2015) four-factor model, and I study three important aspects of the practical application of these models: (1) model choice, (2) model uncertainty, and (3) model predictability. My main findings are three-fold. My first main finding is that there is considerable disagreement about costs of equity capital across the models. My second main finding is that the cost of equity estimates are often extremely noisy, but even more imprecise when factors get added. My third main finding is that the models have some power in forecasting future stock returns, but only when the cost of equity estimates are relatively precise. Although I cannot say based on the findings which model is best, my results highlight the importance of model selection, but also of estimation error in applying popular asset pricing models. Overall, the results raise questions about the usefulness of asset pricing models and indicate a trade-off between the number of factors and estimation errors. Practitioners should (1) evaluate whether the cost of equity estimates are sensitive to the choice of asset pricing model, and (2) realize that a model is useful only when the cost of equity is estimated relatively precisely.

In the fourth chapter, I examine the drivers of stock price variation. This is a key question because the central aim of asset pricing is to understand why stock prices move. I decompose firm-level stock price variation into a component that captures cash flow news and one that captures discount rate news. I show that there is large cross-sectional heterogeneity in the importance of the two drivers of stock prices at the firm and industry level. This is important, because the sources of stock price variation are associated with different characteristics, risks, and expected returns. The relation to expected returns is intuitive, because if discount rates are stationary, then the stock prices that are predominantly driven by discount rate news should also exhibit stationary behavior. This is as opposed to cash flow news-driven stocks as cash flow news does not need to be stationary. I examine two further applications of the decomposition. First, I examine stock price predictability. Although the forecast errors are large, I show that some macroeconomic variables that are frequently used in prediction models are statistically significant in predicting the returns of cash flow news-driven stocks, discount rate news-driven stocks, or both. Next, I investigate stock return co-movement and show that stocks driven by discount rate news exhibit more co-movement than stocks driven by cash flow news. These results suggest that it is important to know why asset prices move because answers to other key questions in asset pricing, at least those relating to stock return predictability and return co-movement, are likely to depend on the relative importance of the two components of stock price variation.

In the fifth chapter, I summarize my main findings and present my conclusions. Overall, this thesis explores various areas in the field of empirical asset pricing. It takes us a step, albeit a small one, closer to the answer to the question of why some assets offer higher returns than others. This thesis also provides a sceptical perspective on the field. Chapter 2 points to the limited ability of popular asset pricing models to explain the cross-section of individual stock returns, and Chapter 3 casts serious doubts on their usefulness for capital budgeting. In future research, my aim is to provide more guidance to investors, managers, and researchers in making investment and corporate finance decisions, and increase our understanding of how financial markets function.

Declaration of Contribution

Chapter 2 is joint work with Marta Szymanowska and Mathijs van Dijk. Together we developed the research idea. I have collected the data and executed the analysis. We have jointly written this chapter. Thomas Conlon and Andrea Tamoni provided us with helpful suggestions.

Chapter 3 is single-authored work, which greatly benefited from feedback from Marta Szymanowska and Mathijs van Dijk. I also received useful comments and suggestions from Dion Bongaerts, Mathijs Cosemans, Pascal François, Bruno Gérard, Rogier Hanselaar, Espen Henriksen, Xavier Mouchette (discussant), Laurens Swinkels, Wolf Wagner, Darya Yuferova, and seminar participants at Erasmus University, Norwegian School of Management (BI), and the 33rd International Conference of the French Finance Association.

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Chapter 2

The Pricing of Systematic Risk Factors Across Horizons*

2.1 Introduction

By now, the conclusion that the classical CAPM fails to explain the cross-section of stock returns is widely accepted. In response to this conclusion, the asset pricing literature has proposed a number of multi-factor asset pricing models that contain additional systematic risk factors. These models include the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model (occasionally augmented with the Pastor and Stambaugh (2003) liquidity factor), and the Fama and French (2015) five-factor model. Despite the popularity of these models, there is an ongoing debate on which risk factors included in these models are priced, and which of these models works better.

An important question that has received relatively little attention to date concerns the horizon over which risks are priced. The common approach in the empirical asset pricing literature is to study monthly returns and estimate Fama and MacBeth (1973) cross-sectional regressions to determine average risk premia associated with different factors. This approach does not allow the risk premium of any factor to be horizon-dependent. Theoretically, Beber, Driessen, and Tuijp (2012) and Brennan and Zhang (2016) develop asset pricing models in which investors have stochastic or heterogeneous horizons, and show that there are important horizon effects in the pricing of risks in such settings.

The question of whether risk premia differ across horizons is important for at least

*This chapter is based on Szymanowska, Van Dijk, and Verbeek (2017) "The Pricing of Systematic Risk Factors Across Horizons." We thank Thomas Conlon and Andrea Tamoni for providing us with helpful suggestions.

two reasons. First, from an academic perspective a true understanding of the nature of asset pricing requires an understanding of the horizon over which economic risks manifest and of the risk premia investors demand as compensation for risks materializing at different horizons. Second, from the perspective of capital budgeting, it is important to study how to discount future cash flows arriving at different horizons. If risk premia depend on the horizon, discounting a stream of future cash flows arriving at different horizons requires a term structure of risk premia, analogous to the term structure of discount rates obtained from discount bonds.

In this paper, we use wavelet analysis to study the relation between risk and return at different horizons. Wavelet analysis is a method that decomposes a time series into components that capture patterns associated with specific time horizons. When applied to risk factors, this method allows us to separate factor risks across horizons. In particular, we decompose the returns on risk factors as well as the excess returns on a set of test assets into five components that are associated with horizons of two to four months, four to eight months, eight to sixteen months, sixteen to 32 months, and 32 to 64 months. Our empirical analysis is based on seven different factors included in the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model augmented with the Pastor and Stambaugh (2003) liquidity factor, and the Fama and French (2015) five-factor model. These factors are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors.

We first show that the decomposition of the factor returns produces components of the risk factors that differ dramatically in their persistence and smoothness. The short-horizon components are very jumpy and highly mean-reverting. The long-horizon components are much more smooth and persistent, indicating that the signals are de-noised, such that events like the bursting of the internet bubble become more apparent than in the non-decomposed, raw factor returns.

We subsequently estimate the risk loadings of the test assets with respect to the factor components at each individual horizon by running time series regressions of the asset return components on the corresponding factor components. The risk loading that is estimated at a short (long) horizon captures the sensitivity of high (low) frequency fluctuations in excess returns to high (low) frequency fluctuations in factor returns. We proceed by evaluating the risk premia associated with the risk loadings at different horizons based on Fama and MacBeth (1973) regressions estimated at each horizon separately, thus deriving a term structure of systematic risk premia. Our sample period is from January 1968 to December 2015. We start in January 1968 because the Pastor and Stambaugh (2003) traded liquidity factor is available from that time.

As pointed out by, for instance, Lewellen, Nagel, and Shanken (2010), the choice of test assets is very important in asset pricing tests. We use random portfolios as our test assets and construct them by sorting individual stocks randomly into 1,000 monthly-rebalanced portfolios in which each stock has an equal weight. We use random portfolios instead of firms to circumvent the problem of missing observations in individual stock return data. This is important, because the wavelet decomposition requires an uninterrupted time series of returns. As shown by Ecker (2013), using random portfolios yields similar Fama and MacBeth (1973) cross-sectional results as using firms. He also shows that one major benefit of using random portfolios is the significant reduction in the measurement errors in the risk loadings, which is one of the main motivations for forming portfolios in the first place. Moreover, the risk premium estimates based on random portfolios are insensitive to the choice between constant and time-varying risk loadings because either type yields qualitatively similar results.

Although we could restrict our sample to firms for which we have an uninterrupted time series of return data, we do not because this would result in a non-representative sample that is heavily biased towards old and stable firms. We also do not use characteristic-sorted portfolios, such as the classic Fama and French (1993) portfolios sorted on size and book-to-market ratio, because it is well-known that risk premium estimates are very sensitive to the choice of test assets (Lewellen, Nagel, and Shanken, 2010; Ahn, Conrad, and Dittmar, 2013; Ecker, 2013). Intuitively, using portfolios that are sorted on a characteristic (such as size) that forms the basis of one of the risk factors (such as SMB) as test assets tends to "favor" that factor in asset pricing tests. Another unattractive feature of characteristic-sorted portfolios is that the risk premium estimates based on Fama and MacBeth (1973) cross-sectional regressions are very sensitive to the choice of using the full sample or a rolling window to estimate the risk loadings (Ecker, 2013).

Our results point to important horizon effects in the pricing of systematic risk. We find that the market and size factors are priced when monthly, raw (non-decomposed) returns are used. Across horizons, we find that these two factors are priced up to sixteen months. In contrast, we find that the value, momentum, liquidity, profitability, and investment factors are not priced at any horizon. This finding is consistent with the literature that generally finds weak firm-level pricing results on risk factors (e.g., Daniel and Titman, 1997; Ecker, 2013; Kamara, Korajczyk, Lou, and Sadka, 2016). Our results show that these factors are also not priced across any of the horizons that we consider.

The study that is probably closest to ours is Kamara, Korajczyk, Lou, and Sadka (2016). They assess the pricing of different factors over different horizons by measuring test asset as well as factor returns over different horizons ranging from one month up to five years, in the spirit of Handa, Kothari, and Wasley (1989) and Jagannathan and Wang (1996). However, their horizon-specific pricing results are different from ours. They find no factors to be priced at the monthly horizon and some factors to be priced at longer horizons. In particular, they find that liquidity risk is priced at a three- to six-month-horizon, that market risk is priced at a six- to twelve-month-horizon, and that the value factor is priced at a two- to three-year horizon. They do not find a significant premium for the size and momentum factor at any horizon.

Although their analysis is interesting and insightful, we believe that our application of wavelet analysis to analyze the pricing of systematic risk factors forms a significant contribution to their study. There are two reasons for this. First, Valkanov (2003) demonstrates that long-horizon regressions, in which the variables are based on a rolling summation of the original time series, can produce significant results irrespective of there being a true structural relation between the variables. Second, an important advantage of wavelet analysis is that it allows us to really separate out short-term versus long-term fluctuations, while compounding returns over different horizons leads to the inclusion of both short-term and long-term fluctuations. Separating out the short- and long-term components of various risk factors enables us to study the importance of low- and high-frequency manifestations of the different systematic risk factors, and the extent to which investors want to be compensated for each of these separate risks.

Our study contributes to a discussion in the literature on whether the term structure of equity risk premia is upward-sloping, flat, or downward-sloping. Most theoretical models imply that the term structure is either flat or upward-sloping (e.g., Campbell and Cochrane, 1999; Bansal and Yaron, 2004; Barro, 2006; Goyal, 2012). Empirically, however, there is evidence that the term structure is downward-sloping (e.g., Van Binsbergen, Brandt, and Koijen, 2012; Weber, 2017). Our study adds to this discussion because our results indicate, contrary to the theoretical predictions and recent empirical findings, that the term structure of the equity premium seems to be non-linear. In fact, we find an upward-sloping term structure of the market factor up to sixteen months, and at longer horizons we find the risk premium to be insignificant. For the size factor we find a term structure that is similarly shaped.

We add to this discussion by taking an approach that does not suffer from the criticisms raised against using dividend strips, which are usually used to study the term structure of the equity premium (Van Binsbergen, Brandt, and Koijen, 2012). In particular, one drawback of using strips is that the results might be driven by microstructure noise (Boguth, Carlson, Fisher, and Simutin, 2012). Another contribution that we make to this literature is that we not only examine the term structure of market risk, but also that of other risk factors. In addition, we employ the entire cross-section in CRSP and cover an extensive sample period (from 1968 until 2015), while the studies that use dividend strips are based on a much smaller cross-section and cover a shorter period of time.

Our study also contributes to the small but growing body of finance research that applies wavelet analysis to the field of asset pricing. We add to studies that focus on the estimation of risk loadings at different horizons (Gençay, Selçuk, and Whitcher, 2003; In and Kim, 2006; Gençay, Selçuk, and Whitcher, 2007; Trimech, Kortas, Benammou, and Benammou, 2009; In and Kim, 2013) by instead focusing on the estimated risk premia at different horizons. In addition, while this literature mainly studies the CAPM market factor, and sporadically also the Fama and French (1993) size and value factors and the Carhart (1997) momentum factor, we examine other factors as well. Moreover, while this literature usually considers a small and specific set of test assets, we consider the full CRSP file. The literature has also used wavelet analysis to relate risk factors to innovations in state variables (In and Kim, 2007), and to study other macroeconomic variables, such as consumption growth, on a horizon-by-horizon basis (Ortu, Tamoni, and Tebaldi, 2013; Bandi and Tamoni, 2017). However, to the best of our knowledge, our study is the first to apply wavelet analysis to the study of the pricing of systematic risk factors from several widely used multi-factor asset pricing models at different horizons.

2.2 The Relation Between Risk and Return Across Different Horizons

In this paper, we are interested in studying the relation between risk and return at different horizons. Traditionally, this relation is evaluated using the Fama and MacBeth (1973) cross-sectional regression approach where loadings to risk factors and prices of risk are estimated using the time series and cross-section of excess returns on test assets and factors. In this section, we describe how we perform this analysis on a horizon-by-horizon basis. This allows us to assess whether risk factors we analyze are particularly relevant at certain horizons. To compute horizon-specific risk loadings and prices of risk, we use the wavelet approach to decompose the time series of excess returns on the test assets and factors across different horizons. Subsequently, we estimate horizon-specific loadings and prices of risk using the components. We explain our method in detail below.

2.2.1 Wavelet Decomposition

We use wavelet decomposition because it allows us to truly separate out the contribution to risk of distinct horizons from our time series. In particular, our decomposition allows us to study long-horizon effects that are distinct from short-horizon fluctuations. This approach is fundamentally different from examining horizon effects by first aggregating the returns on test assets and factors over particular horizons and then resorting to the traditional Fama and MacBeth (1973) approach (e.g., Kamara, Korajczyk, Lou, and Sadka, 2016). In this subsection, we outline the basic concepts of the wavelet transform we use. We refer the reader to Gençay, Selçuk, and Whitcher (2002) and In and Kim (2013) for a more extensive discussion of applications of wavelet analysis in finance and economics.

To decompose the time series of excess returns on our test assets and factors, we use the maximum overlap discrete wavelet transform (MODWT) with the Daubechies (1992) least asymmetric filter with eight lags (LA8). We choose MODWT mainly because of its ability to handle any sample size, increased resolution at longer horizons, and because it is a more asymptotically-efficient variance estimator than the alternative DWT. We use the LA8 filter because it is much closer to an ideal band-pass filter than the Haar filter (Gençay, Selçuk, and Whitcher, 2003). In robustness tests, we find similar results with the DWT and Haar filter.

Wavelet analysis is different from the more classical spectral analysis tools, which are also used to study market dynamics across investment horizons (e.g., Chaudhuri and Lo, 2016). Spectral analysis is used to describe a time series process as a function of frequency. While spectral analysis does not have a time dimension, the wavelet transform preserves information both in time and frequency. In contrast to wavelets, spectral analysis assumes stationarity and regular periodicity in the time series. Those assumptions are often not reasonable for financial data.

Our wavelet decomposition separates a time series $\boldsymbol{x}$ of length T, which could be a time series of either excess test asset returns or factor returns, into a linear combination of J components with different frequencies (or time horizons):

$$\boldsymbol{x} = \sum_{j=1}^{J} \widetilde{\mathcal{W}}_j' \widetilde{\boldsymbol{w}}_j + \widetilde{\mathcal{V}}_J' \widetilde{\boldsymbol{v}}_J \tag{2.1}$$

where $\widetilde{\boldsymbol{w}}_j$ is a vector containing the wavelet coefficients, $\widetilde{\boldsymbol{v}}_J$ is a vector containing the scaling coefficients, and $\widetilde{\mathcal{W}}$ and $\widetilde{\mathcal{V}}$ are matrices that define the MODWT. The wavelet coefficients capture innovations in $\boldsymbol{x}$ at horizons that correspond to time intervals of $[2^j, 2^{j+1}]$ for $j < J$. The scaling coefficients capture the long-term trend in $\boldsymbol{x}$, which is determined by the sample average over horizons of more than 2^J periods. The frequency interpretation for these components is summarized in Table 2.1.

Table 2.1. Frequency Interpretation

Component	Frequency (time horizon)
$\widetilde{w}_1$	2 – 4 months
$\widetilde{w}_2$	4 – 8 months
$\widetilde{w}_3$	8 – 16 months
$\widetilde{w}_4$	16 – 32 months
$\widetilde{w}_5$	32 – 64 months
$\widetilde{v}_5$	> 64 months

In our main analysis, we use five components. This choice reflects a trade-off between understanding the risk-return relation at longer horizons and the exclusion of observations as a result of boundary conditions. Boundary conditions play an important role when the time series $\boldsymbol{x}$ has finite length. Since we do not want to make unrealistic assumptions about boundary conditions, we remove their effect by ignoring the first $(L-1)(2^j-1)$ observations for every component in $\widetilde{\boldsymbol{w}}_j$, where L is the length of the wavelet filter. Excluding observations is problematic because it leads to more estimation error in the risk loadings and, consequently, in the risk premia. Extracting five components results in the exclusion of $7 \times (2^5 - 1) = 217$ observations in the fifth component due to boundary conditions. Extracting six components would result in the exclusion of $7 \times (2^6 - 1) = 441$ observations in the longest term wavelet coefficient, which amounts to almost all observations. Our choice to extract five components is consistent with the literature in which usually four to six components are extracted (e.g., Gençay, Selçuk, and Whitcher, 2003; In and Kim, 2006; Trimech, Kortas, Benammou, and Benammou, 2009; In and Kim, 2013; Ortu, Tamoni, and Tebaldi, 2013).

2.2.2 Horizon-Specific Risks

Following, among others, Gençay, Selçuk, and Whitcher (2003), In and Kim (2013), Boons and Tamoni (2015), and Bandi and Tamoni (2017), we evaluate the risk-return relation over different horizons using the wavelet coefficients defined above. An important characteristic of our wavelet transform is its ability to decompose the variance of a time series as well as the covariance between two time series. Therefore, we can define the horizon-specific factor loading as:

$$\beta_i^{(j)} = \frac{\mathrm{Cov}(R_{i,t}^{(j)}, F_t^{(j)})}{\mathrm{Var}(F_t^{(j)})} \tag{2.2}$$

where $R_{i,t}^{(j)}$ is the jth component of excess returns on asset i, and $F_t^{(j)}$ is the vector with the jth components of the returns on the factors. We estimate those loadings in the following regression, using components of returns on assets and factors:

$$R_{i,t}^{(j)} = \alpha_i^{(j)} + \boldsymbol{F}_t^{(j)\prime}\boldsymbol{\beta}_i^{(j)} + \varepsilon_{i,t}^{(j)}, \text{for } j = 1, 2, ..., J \tag{2.3}$$

Thus, $\hat{\boldsymbol{\beta}}_i^{(j)}$ measures the horizon-specific loadings of a security on the risk factors.

Next, we assess whether the horizon-specific risk loadings capture cross-sectional variation in asset returns by running the following Fama and MacBeth (1973) cross-sectional regression at each point in time:

$$R_{i,t} = \Lambda_0^{(j)} + \hat{\boldsymbol{\beta}}_i^{(j)\prime}\boldsymbol{\Lambda}_t^{(j)} + u_{i,t}^{(j)}, \text{for } j = 1, 2, ..., J \tag{2.4}$$

Note that we use non-decomposed returns as the dependent variable, because we are interested in how factor loadings (here estimated across different horizons) are related to expected returns. We do not use the return components as the dependent variable because our method allows us to decompose return variance, not return levels. We estimate the risk premia at horizon j by $\bar{\boldsymbol{\Lambda}}^{(j)} = \frac{1}{T}\sum_{t=0}^{T-1}\hat{\boldsymbol{\Lambda}}_t^{(j)}$. Thus, horizon effects might not only show up in the risk loadings, but also in the estimated risk premia.

This empirical decomposition can be motivated by recent theoretical models. For instance, Brennan and Zhang (2016) examine a model in which investors have a stochastic investment horizon and returns are serially dependent. They show that, in this setting, expected returns are a weighted sum of horizon-specific risk loadings times the corresponding market risk premia. This is contrary to the fixed-horizon CAPM that assumes the risk loadings and risk premium to be horizon-invariant. Our wavelet decomposition leads to a similar representation of expected returns as in Brennan and Zhang (2016) because it gives us horizon-specific risk loadings and risk premia per factor. Hence we extend their set-up by examining the horizon effects that are present in multiple risk factors as opposed to only the market factor.

2.3 Risk Factors Across Horizons

We retrieve the factors included in the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model, and the risk-free rate from Ken French‘s Data Library.[1] We obtain the Pastor and Stambaugh (2003) traded liquidity factor from WRDS.

We present summary statistics on the decomposition of the risk factors in Table 2.2. Specifically, we report the mean and variance of the monthly factor returns, and the (relative) wavelet energies. As shown in Gençay, Selçuk, and Whitcher (2003), our wavelet transformation preserves the variance of the original time series, and thus we can decompose the variance in the following way:

$$\|\boldsymbol{x}\|^2 = \sum_{j=1}^{J}\left\|\widetilde{\boldsymbol{w}}_j\right\|^2 + \left\|\widetilde{\boldsymbol{v}}_J\right\|^2 \tag{2.5}$$

where $\|\boldsymbol{x}\|^2$ is the variance of the time series $\boldsymbol{x}$, $\left\|\widetilde{\boldsymbol{w}}_j\right\|^2$ captures the energy from changes at horizon j and $\left\|\widetilde{\boldsymbol{v}}_J\right\|^2$ captures the energy from the residual, long-term component. This equation shows that the variance decomposition allows us to determine whether

[1] We thank Ken French for making the data available at:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 2.2. Summary Statistics Risk Factors

This table presents summary statistics on the decomposition of seven risk factors. The risk factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. The momentum factor is from Carhart (1997), the liquidity factor is the traded liquidity factor from Pastor and Stambaugh (2003), and the remaining factors are from the Fama and French (2015) five-factor model. We apply the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the risk factors. We exclude $7 \times (2^j - 1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract six components. We present the average (Avg), variance (Var), scaled sum of squared wavelet coefficient vectors (Energies), and energies as a fraction of the summed energies of all factor components (Relative Energies). Energies are calculated for wavelet coefficients 1 to 6 ($\widetilde{w}_1$ to $\widetilde{w}_6$). The energies are scaled by $N2^{-j}$ for comparison purposes. The sample period is from January 1968 to December 2015.

			Energies						Relative Energies					
Factor	Avg	Var	$\widetilde{w}_1$	$\widetilde{w}_2$	$\widetilde{w}_3$	$\widetilde{w}_4$	$\widetilde{w}_5$	$\widetilde{w}_6$	$\widetilde{w}_1$	$\widetilde{w}_2$	$\widetilde{w}_3$	$\widetilde{w}_4$	$\widetilde{w}_5$	$\widetilde{w}_6$
MKT	0.48	20.87	18.77	21.70	21.50	20.33	11.85	2.14	0.19	0.22	0.22	0.21	0.12	0.02
SMB	0.19	9.44	8.62	9.88	9.68	6.26	3.98	2.06	0.21	0.24	0.23	0.15	0.10	0.05
HML	0.36	8.36	6.69	8.22	10.03	8.98	14.19	2.11	0.13	0.16	0.20	0.18	0.28	0.04
WML	0.68	18.95	17.32	20.44	18.25	20.10	9.91	1.57	0.20	0.23	0.21	0.23	0.11	0.02
LIQ	0.42	12.29	10.89	13.70	16.48	6.04	7.14	1.14	0.19	0.23	0.28	0.10	0.12	0.02
RMW	0.26	5.33	4.30	5.73	5.79	5.38	9.02	0.84	0.14	0.18	0.19	0.17	0.29	0.03
CMA	0.35	4.09	3.42	3.66	4.81	3.54	3.47	1.04	0.16	0.17	0.23	0.17	0.17	0.05

most energy is captured by either the short- or long-term components, or whether it is equally distributed across all components of the original time series.

The first two columns of Table 2.2 indicate that there are considerable differences across the factors in terms of their average returns and variances. Momentum clearly dominates in terms of average return, with a factor realization of 0.68% per month. On the other end, the size factor delivers the smallest return of only 0.19% per month. We see more variation across factors in terms of their variance. Momentum together with the market factor have the highest variance, while the variance of the more recently proposed profitability and investments factors is four times smaller.

In the remaining columns we examine the horizon-specific components of the factors by looking at their energy decomposition across horizons. The results for the absolute and relative wavelet energies show that the differences in scaled energies across horizons are relatively minor at the short and intermediate horizons, and that the energies are substantially lower at the long-term horizons. The sixth component of all factors exhibits virtually no variation over time, suggesting that estimating risk loadings at the corresponding horizon is problematic. This prompted us to decide to focus on the first five components. We also note that there are some minor differences in the energy distributions across factors. For example, the size and liquidity factors have slightly more energy contained at shorter horizons, while the value, profitability, and investment factors slightly dominate at longer horizons.

Using a different methodology, Kamara, Korajczyk, Lou, and Sadka (2016) also analyze the importance of risks at different horizons. They examine the variance ratios of the risk factors by using continuously compounded returns over varying horizons. This is different from our approach because their long-horizon factors also include short-term effects while our decomposition separates the two. They find that liquidity risk is greater in the short-term as the liquidity factor has negative serial correlation, and that value risk is greater in the long term because it has positive serial correlation.[2] They do not find evidence suggesting that market, size, and momentum risk is greater at particular horizons. Thus, our results are largely in line

[2]We note that Kamara, Korajczyk, Lou, and Sadka (2016) use the non-traded liquidity factor of Pastor and Stambaugh (2003), while we use the traded factor.

with Kamara, Korajczyk, Lou, and Sadka (2016).

To illustrate how the decomposition works and to show that it reveals insights into the dynamics of factor returns, we plot the evolution of the factor returns and their components in Figure 2.1. In each figure, the raw return series is presented first, followed by the wavelet coefficients. Note that the first $7 \times (2^j - 1)$ observations are excluded because they are affected by boundary conditions. The components are circularly shifted to align them better with the raw data in calendar time (Gençay, Selçuk, and Whitcher, 2003).

The figure clearly shows that the wavelet coefficients become smoother for the components that capture variation over increasingly longer horizons. One interpretation of the series becoming smoother for longer horizons is that the signals are de-noised, since short-term fluctuations are filtered out. The coefficients that capture variation at longer horizons are able to identify events that might be obscured in the raw series or the short-horizon components. For example, the fifth wavelet coefficient of the market factor clearly identifies the bursting of the internet bubble in 2001 and the global financial crisis in 2007 and 2008. The coefficients also reveal a size crash in 1998, a momentum crash in 2009 (Daniel and Moskowitz, 2016), and a spike in the liquidity and profitability factors around 2001. By comparison, these events are harder to detect in the raw data series or one of the short-term components. Hence, all components capture an important part of the variation in our original series, and the differences between the components allow us to focus on horizon-specific dynamics that may be obscured in the aggregate series.

Given the relative smoothness of the longest-horizon components of each of the factors, one concern could be that the long-horizon components of several different risk factors capture the same underlying long-term trend. We therefore analyze whether our decomposition affects the correlation structure between the factors. Table 2.3 presents correlations between the factors, estimated for the raw series as well as the components.

In general, the magnitudes of the correlation coefficients vary only slightly across the components, and the statistical significance decreases with the increasing horizon

Figure 2.1. Wavelet Decomposition of Risk Factors

This figure shows the time series evolution of seven non-decomposed (raw) and decomposed risk factors. The risk factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. The momentum factor is from Carhart (1997), the liquidity factor is the traded liquidity factor from Pastor and Stambaugh (2003), and the remaining factors are from the Fama and French (2015) five-factor model.f We apply the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the risk factors. We exclude $7 \times 2^j - 1$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. To better align the components with the raw data in calendar time, we shift $\widetilde{w}_1$, $\widetilde{w}_2$, $\widetilde{w}_3$, $\widetilde{w}_4$, and $\widetilde{w}_5$ by 5, 11, 25, 53, and 109 months to the left, respectively. The sample period is from January 1968 to December 2015.

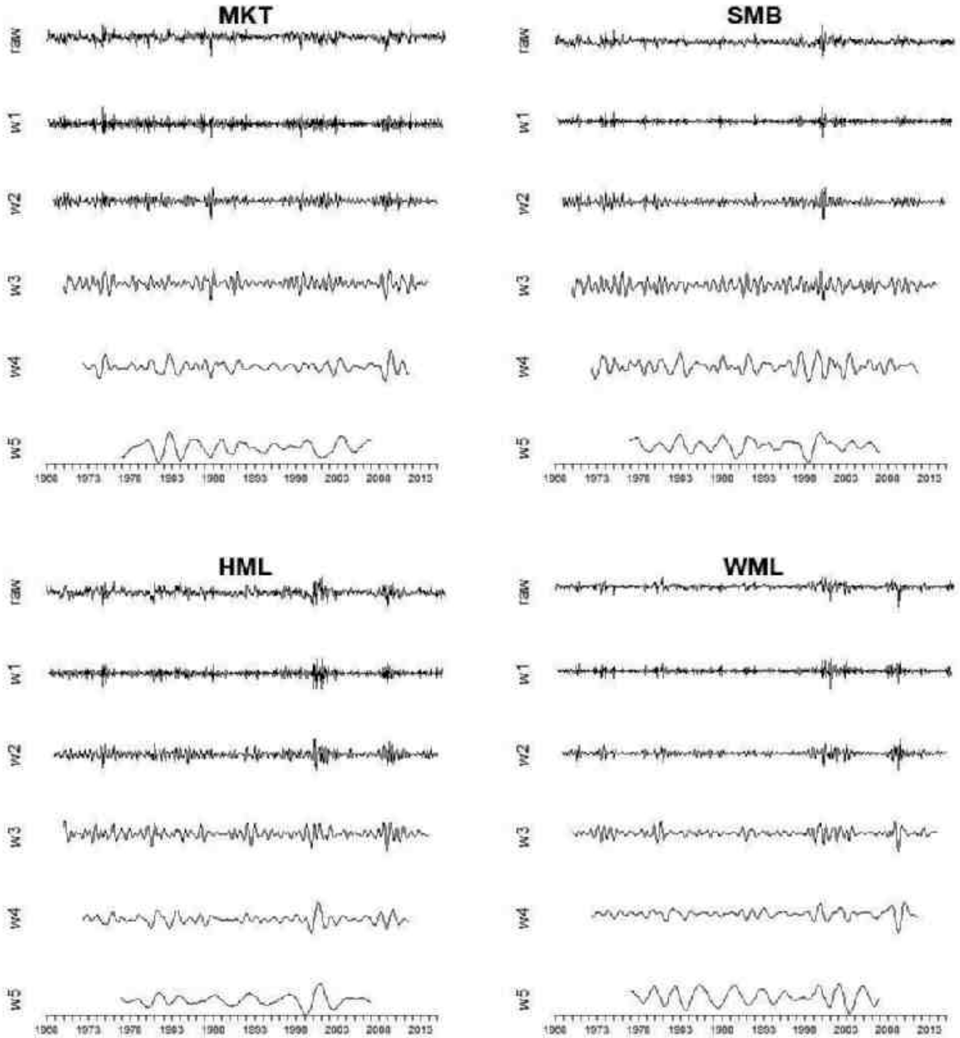

Figure 2.1. Wavelet Decomposition of Risk Factors *(continued)*

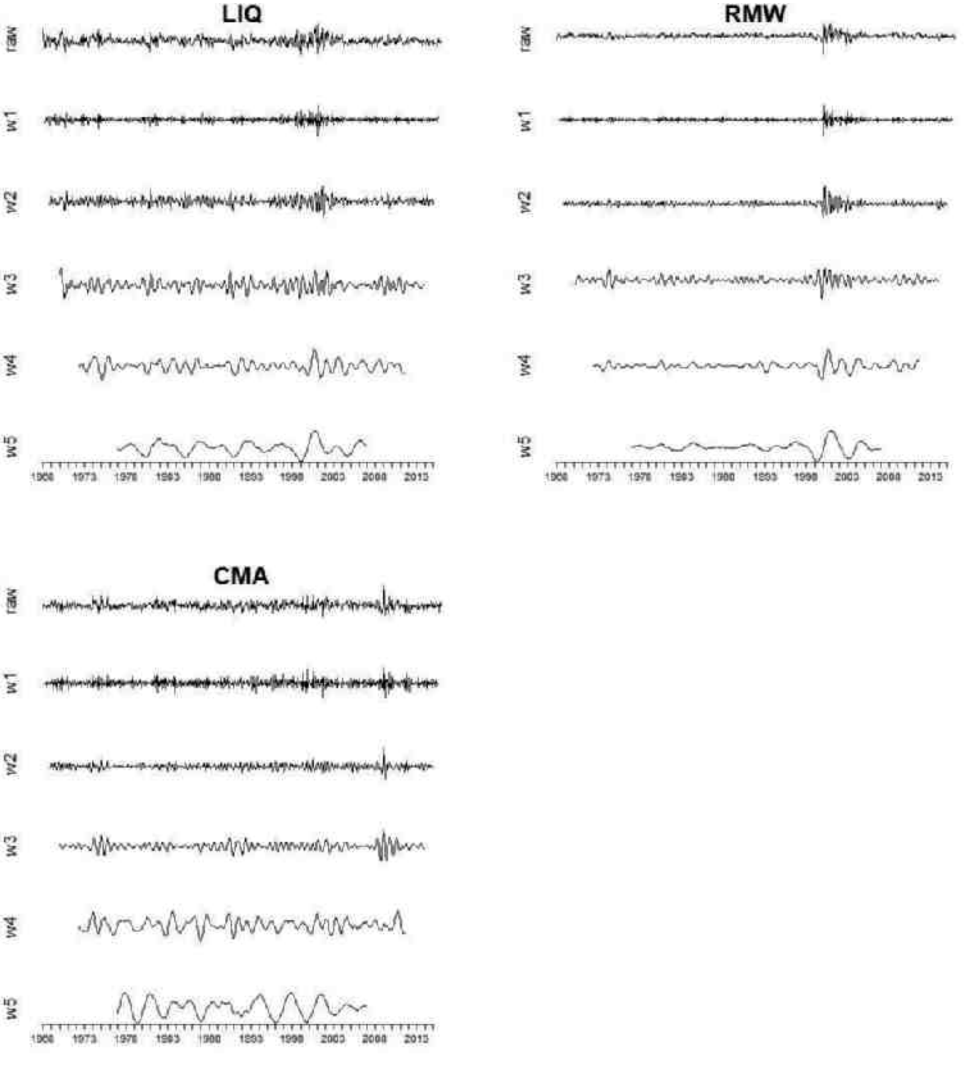

Table 2.3. Correlations Between Risk Factors at Different Horizons

This table presents Pearson correlations and wavelet correlations between seven risk factors. The risk factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. The momentum factor is from Carhart (1997), the liquidity factor is the traded liquidity factor from Pastor and Stambaugh (2003), and the remaining factors are from the Fama and French (2015) five-factor model. We apply the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the risk factors. We exclude $7 \times (2^j - 1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. Results are presented for the non-decomposed series (Raw), and wavelet coefficients 1 to 5 ($\widetilde{w}_1$ to $\widetilde{w}_5$). The sample period is from January 1968 to December 2015. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

		SMB	HML	WML	LIQ	RMW	CMA
Raw	MKT	0.26***	−0.28***	−0.14***	−0.07	−0.24***	−0.40***
$\widetilde{w}_1$		0.10	−0.31***	−0.07	−0.09	−0.22***	−0.40***
$\widetilde{w}_2$		0.38***	−0.25***	−0.21**	−0.02	−0.25***	−0.37***
$\widetilde{w}_3$		0.62***	−0.21*	−0.21*	0.05	−0.25**	−0.41***
$\widetilde{w}_4$		0.44***	−0.30*	−0.22	−0.14	−0.40**	−0.43***
$\widetilde{w}_5$		0.24	−0.45*	0.13	−0.39	−0.50**	−0.26
Raw	SMB		−0.10**	−0.04	−0.02	−0.37***	−0.08**
$\widetilde{w}_1$			−0.08	0.00	−0.03	−0.45***	−0.03
$\widetilde{w}_2$			−0.17**	−0.09	−0.02	−0.48***	−0.16*
$\widetilde{w}_3$			−0.10	−0.11	−0.12	−0.23**	−0.22*
$\widetilde{w}_4$			−0.24	0.05	0.17	−0.38**	−0.21
$\widetilde{w}_5$			0.15	−0.05	−0.26	0.00	0.13
Raw	HML			−0.18***	0.01	0.10**	0.70***
$\widetilde{w}_1$				−0.12**	0.12**	0.13**	0.69***
$\widetilde{w}_2$				−0.19**	−0.05	0.13	0.67***
$\widetilde{w}_3$				−0.27**	−0.18	−0.13	0.75***
$\widetilde{w}_4$				−0.24	0.18	0.35**	0.73***
$\widetilde{w}_5$				−0.31	0.16	0.64***	0.72***
Raw	WML				−0.01	0.11**	0.01
$\widetilde{w}_1$					−0.11*	0.14**	0.05
$\widetilde{w}_2$					0.08	0.16*	0.03
$\widetilde{w}_3$					0.05	0.01	0.07
$\widetilde{w}_4$					−0.08	−0.04	0.03
$\widetilde{w}_5$					−0.09	−0.06	−0.28
Raw	LIQ					0.03	0.02
$\widetilde{w}_1$						0.03	0.08
$\widetilde{w}_2$						−0.04	0.00
$\widetilde{w}_3$						0.07	−0.12
$\widetilde{w}_4$						0.03	0.22
$\widetilde{w}_5$						0.37	−0.09
Raw	RMW						−0.01
$\widetilde{w}_1$							0.00
$\widetilde{w}_2$							0.02
$\widetilde{w}_3$							−0.11
$\widetilde{w}_4$							0.21
$\widetilde{w}_5$							0.28

due to the relatively larger estimation errors as a result of a smaller number of independent observations that are available for the long-term components. We conclude that, although there is variation in the correlation coefficients across horizons, the correlation structure between the factors is largely preserved by the decomposition. This is important for our subsequent analyses of the loadings and prices of risk across different horizons.

2.4 The Pricing of Risk Across Horizons

We now turn to our main analysis of the risk-return trade-off across different horizons. To this end, we study whether horizon-specific loadings can explain cross-sectional variation in our test asset returns and whether their explanatory power varies with the horizon.

Our test assets are randomly generated portfolios based on individual firms. Although the risk premium estimates based on random portfolios are very similar to those based on individual firms (Ecker, 2013), there are some important advantages to using random portfolios. One of them is that random portfolios provide an uninterrupted time series of return data, which our decomposition method requires. Another benefit of random portfolios is that the risk loadings are relatively precisely estimated, and that the results are insensitive to whether the risk loadings are estimated on the full-sample or on a rolling window basis. Rolling window risk loadings are often used instead of full sample risk loadings to capture a firm's changing risk profile over time. However, since the expected risk profile of each portfolio is reset to the cross-sectional average risk profile every month, there is no reason to expect that using rolling window risk loadings yields different pricing results than using full sample risk loadings. In our analysis, we use 1,000 monthly-rebalanced random portfolios and compute equally-weighted returns. As shown in Ecker (2013), the Fama and MacBeth (1973) regression results are not sensitive to the number of portfolios. We use equal and not value weighting so as not to undermine the comparability with the standard firm-level Fama and MacBeth (1973) results.

We retrieve monthly stock return data from CRSP. We use ordinary common shares (share codes 10 and 11) that are listed on the NYSE, AMEX, and NASDAQ (exchange codes 1, 2, and 3). We require prices to be at least \$1, and we also require at least 24 return observations to be available for a firm to be included in the sample. We impose this restriction in order to obtain full-sample firm-level risk loading estimates that are reasonably precise. The sample period starts in January 1968 and ends in December 2015.

Table 2.4 reports annualized average risk premium estimates based on both non-normalized and normalized risk loadings, t-statistics, and average R^2s from running cross-sectional Fama and MacBeth (1973) regressions of our test asset returns on horizon-specific loadings for all four models.[3] We present risk premium estimates based on normalized risk loadings for comparison purposes. This is necessary because, as we show later, there are large differences in the distribution of risk loadings across horizons and risk factors. We normalize by setting the cross-sectional variance of the risk loadings to unity.

We first examine the risk premium estimates for individual firms based on raw data and compare them with those based on random portfolios. Examining the risk premium estimates based on individual firms, we find that the market and size factors have significant prices of risk in all factor models. The corresponding Newey and West (1987) t-statistics are around 2.0 for both factors. We do not find significant prices of risk related to the value, momentum, liquidity, profitability, and investment factors in any of our specifications. These weak pricing results based on individual firms are consistent with the literature. For instance, Kamara, Korajczyk, Lou, and Sadka (2016) use rolling window risk loadings and do not find any factor to be priced at the monthly horizon. Ecker (2013) uses full-sample risk loadings and finds, like us, the market and size factors to be priced. We note that most studies that find the other factors to be priced (e.g., Fama and French, 2015) use characteristic-sorted portfolios instead of individual firms as test assets.[4]

[3]Since the risk loadings must be estimated, one might be concerned about the errors-in-variables (EIV) problem. To alleviate this concern, we also estimate Shanken (1992) t-statistics and report the results in Appendix 2.A. Our main conclusions do not change with these alternative t-statistics.

[4]In fact, we have tried various characteristic-sorted portfolios from Ken French's Data Library, among others. In line with the findings in the literature, we find that the pricing results are very sensitive to the choice of test assets. It is not uncommon to find that some factors have positive significant risk premium estimates when using one set of test assets and negative significant estimates when using another. Often, we find factors to be priced when the variable on which the factor is

Table 2.4. Monthly Cross-Sectional Fama-MacBeth Regressions

This table presents results from cross-sectional Fama and MacBeth (1973) regressions based on raw and horizon-specific risk loadings. The portfolio returns are from 1,000 random portfolios. We use the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model augmented with the Pastor and Stambaugh (2003) traded liquidity factor, and the Fama and French (2015) five-factor model. The factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. We apply the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the portfolio excess returns and risk factors. We exclude $7 \times (2^j - 1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. We obtain full sample risk loadings on a horizon-by-horizon basis and run cross-sectional Fama and MacBeth (1973) regressions. We report annualized risk premium estimates based on non-normalized and normalized risk loadings, corresponding Fama and MacBeth (1973) t-statistics with Newey and West (1987) adjustment, and average cross-sectional R^2s. Results are presented for risk loadings that correspond to aggregate risk loadings (Firms and Portf.), and horizon-by-horizon risk loadings ($\widetilde{w}_1$ to $\widetilde{w}_5$). The sample period is from January 1968 to December 2015. We present average results based on 100 independent simulation runs.

		CAPM		FF3				C4 + LIQ						FF5					
		MKT	R^2	MKT	SMB	HML	R^2	MKT	SMB	HML	WML	LIQ	R^2	MKT	SMB	HML	RMW	CMA	R^2
Risk premia	Firms	6.66	3.20	5.73	3.29	−2.11	6.91	5.41	3.15	−1.94	1.22	−0.84	9.28	5.42	3.21	−2.03	−1.56	−0.79	9.42
Non-norm.	Portf.	6.97	0.36	5.75	4.58	−1.73	1.03	5.24	4.51	−1.88	−2.02	−1.08	1.60	5.78	4.48	−1.54	−1.92	−0.82	1.66
Risk premia	Portf.	0.58	0.36	0.50	0.69	−0.27	1.03	0.44	0.67	−0.29	−0.23	−0.11	1.60	0.52	0.65	−0.31	−0.42	−0.22	1.66
Normalized	$\widetilde{w}_1$	0.33	0.33	0.32	0.42	−0.22	0.95	0.30	0.42	−0.21	−0.18	−0.05	1.53	0.31	0.39	−0.18	−0.45	−0.20	1.54
	$\widetilde{w}_2$	0.49	0.32	0.50	0.59	−0.21	0.95	0.49	0.60	−0.21	−0.05	−0.07	1.51	0.51	0.60	−0.27	−0.34	−0.26	1.55
	$\widetilde{w}_3$	0.55	0.30	0.65	0.68	−0.22	0.88	0.65	0.69	−0.23	−0.06	−0.13	1.43	0.61	0.66	−0.26	−0.40	−0.28	1.46
	$\widetilde{w}_4$	0.43	0.29	0.50	0.15	−0.31	0.85	0.45	0.17	−0.32	−0.24	−0.12	1.39	0.50	0.13	−0.34	−0.36	−0.24	1.40
	$\widetilde{w}_5$	0.37	0.29	0.36	0.31	−0.25	0.84	0.33	0.26	−0.24	0.04	−0.27	1.39	0.40	0.32	−0.35	−0.21	−0.24	1.40
Newey-West	Firms	2.24		2.16	2.02	−1.18		2.19	1.95	−1.09	0.44	−0.52		2.09	2.08	−1.13	−1.07	−0.76	
t-statistics	Portf.	1.99		1.68	2.24	−0.81		1.61	2.19	−0.90	−0.57	−0.48		1.74	2.28	−0.78	−1.14	−0.69	
	$\widetilde{w}_1$	2.10		1.96	1.99	−1.03		1.86	1.95	−0.95	−0.82	−0.35		1.83	1.93	−0.77	−1.86	−0.80	
	$\widetilde{w}_2$	3.13		3.24	2.75	−1.15		3.51	2.66	−1.27	−0.26	−0.51		3.77	3.09	−1.30	−1.45	−1.29	
	$\widetilde{w}_3$	1.90		1.88	2.22	−0.82		1.89	2.18	−0.89	−0.19	−0.66		1.91	2.26	−0.69	−1.14	−0.87	
	$\widetilde{w}_4$	0.82		0.82	0.31	−0.53		0.77	0.35	−0.53	−0.35	−0.31		0.82	0.28	−0.48	−0.58	−0.37	
	$\widetilde{w}_5$	0.68		0.63	0.53	−0.36		0.59	0.48	−0.33	0.08	−0.52		0.69	0.55	−0.43	−0.29	−0.32	

Comparing the firm results to the random portfolio results, we find that the risk premium estimates and levels of statistical significance are of similar magnitudes. The observation that the two sets of test assets yield similar pricing results is in line with our motivation to use them. In terms of economic significance, the annualized risk premium is around 5 – 7% for the market factor and around 3 – 5% for the size factor, when either individual firms or random portfolios are used as test assets. We note that the adjusted R^2s for random portfolios are substantially lower than those for firms. This is because the cross-sectional variation in the risk loadings relative to the variation in excess returns is substantially reduced when the random portfolios are formed.

Next, we study the pricing of risk factors across horizons using the 1,000 random portfolios as our test assets. Looking across different horizons we find that the market and size factors are also priced at horizons of two to sixteen months. All the other risk factors are not associated with a positive price of risk at any of the horizons that we consider. This is unlike consumption growth, for instance, which is not priced when sampled on a quarterly frequency, but is priced when the risk loadings are estimated with respect to the components corresponding to horizons of two to eight years (Bandi and Tamoni, 2017). Our findings are also in contrast to Kamara, Korajczyk, Lou, and Sadka (2016), who find none of the factors to be priced at the monthly horizon, but find the market, value, and liquidity factors to be priced at specific horizons. Although we find that the cross-sectional R^2s tend to decrease slightly with horizon, the differences in the R^2s across the horizons and models are rather small.

In terms of economic significance, we see that the compensation per year for a one cross-sectional standard deviation change in the raw risk loadings is around 0.44% – 0.58% for the market factor and 0.65% – 0.69% for the size factor. The compensations for risk change, although not substantially, across the horizons that we consider. The compensation per year for a one cross-sectional standard deviation

based is also used for sorting (such as testing whether HML is priced into portfolios sorted on size and book-to-market ratio). Across horizons, we find that the pricing results are similarly sensitive to the choice of sorting variables. These results are available from the authors on request.

change in the market risk loading increases from 0.30% − 0.33% at the two-to-four-month horizon to 0.55% − 0.65% at the eight-to-sixteen-month horizon. The compensation corresponding to the size factor is 0.39% − 0.42% at the two-to-four-month horizon and 0.66% − 0.69% at the eight-to-sixteen-month horizon. Thus, our results suggest that up to sixteen months the term structure of the market and SMB risk premium is upward-sloping. At longer horizons, however, the risk premium estimates are statistically insignificant.

Using a new methodology, we add to the debate about the shape of the term structure of the market risk premium. Our results are different from Van Binsbergen, Brandt, and Koijen (2012) and Weber (2017) as we do not find a downward-sloping term structure. Instead, we conclude from our results that the term structure, when evaluated over the entire spectrum of horizons, has a non-linear shape. In particular, the term structure of the equity premium seems to be upward sloping up to sixteen months, after which it is not statistically different from zero.

As can be seen in Table 2.4, our conclusions regarding the horizon of each of the risk premia are consistent across the different asset pricing models. As a robustness check, we use the Hou, Xue, and Zhang (2015) four-factor model,[5] and obtain results similar to those obtained for the Fama and French (2015) five-factor model. We also use the Carhart (1997) four-factor model without augmenting the Pastor and Stambaugh (2003) liquidity factor, and obtain similar results. Moreover, our results are also robust with respect to the choice of the decomposition method and the wavelet filter applied. In particular, we re-estimate our main results using the DWT to address concerns about possible correlation between the MODWT components. We also assess whether our results change if we use another wavelet filter, namely the Haar filter. For all of these specifications, we obtain qualitatively similar results.[6]

[5] The Hou, Xue, and Zhang (2015) model has a market, size, profitability, and investment factor. We have obtained these factors from the authors. The factors of Hou, Xue, and Zhang (2015) are available from January 1972 to December 2013.

[6] These results are reported in Appendix 2.A.

2.5 Horizon-Specific Risk Loadings

In this section, we analyze the horizon-specific risk loadings that are estimated in the first step of our Fama and MacBeth (1973) regressions to examine whether horizons effects are also present there. Table 2.5 presents the estimates of the full sample time series regressions of our test asset returns on the returns on each factor, estimated separately for each horizon as well as for the non-decomposed, raw returns. We do not consider rolling window regressions because removing boundary conditions would result in a small number of (independent) observations for estimating risk loadings, especially at longer horizons, which would result in less precisely estimated risk loadings. Moreover, it is not obvious how the horizon-specific risk loadings should be matched with raw returns in calendar time. If we could estimate rolling window risk loadings, we expect to find similar results since Ecker (2013) shows that the pricing results (based on non-decomposed returns) are robust to different ways of estimating risk loadings. This insensitivity to how the risk loadings are estimated is also a reason why we have selected random portfolios as our test assets.

Table 2.5 presents statistics on the risk loadings. In Panel A, we report the mean and cross-sectional standard deviation of the estimated risk loadings, and in Panel B we report the mean Newey and West (1987) t-statistics and the fraction of the risk loadings that are statistically different from zero. To conserve space, we only present the results of risk loadings on all risk factors of the Fama and French (2015) five-factor model, and the momentum and liquidity factors of the Carhart (1997) four-factor model augmented with the liquidity factor of Pastor and Stambaugh (2003).

We find that it is often hard to obtain risk loadings that are statistically significant. Table 2.5 shows that a substantial fraction of the risk loading estimates are insignificant when individual firms are used as test assets. Only 64% and 48% of the risk loading estimates are significant for the market and size factor, respectively, and most of the risk loadings corresponding to the other factors are insignificant. We attempt to alleviate the problem of using insignificant risk loadings by using random portfolios, which allow us to estimate risk loadings that are more precise as idiosyncratic risk is reduced through diversification. In line with this reasoning, our results

Table 2.5. Raw and Horizon-Specific Risk Loadings

This table presents risk loadings of raw and decomposed excess returns on 1,000 random portfolios. Results are presented for all the risk factors of the Fama and French (2015) five-factor model, and the momentum and liquidity factors of the Carhart (1997) four-factor model augmented with the liquidity factor of Pastor and Stambaugh (2003). The factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. The results are for the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8). We exclude $7\times(2^j-1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. We then estimate full sample risk loadings on a horizon-by-horizon basis. The presented risk loadings correspond to non-decomposed (Firms and Portfolios) and decomposed ($\widetilde{w}_1$ to $\widetilde{w}_5$) excess returns and risk factors. In Panel A, we present the mean and cross-sectional standard deviation of the estimated risk loadings, and in Panel B we present the mean Newey and West (1987) t-statistics and the fraction of the risk loading estimates that are statistically significant at the 5% level. The sample period is from January 1968 to December 2015. We present average results based on 100 independent simulation runs.

		MKT	SMB	HML	WML	LIQ	RMW	CMA
Panel A. Risk loadings								
Mean	Firms	0.93	0.95	0.14	−0.14	0.00	−0.25	−0.13
	Portfolios	0.97	0.86	0.18	−0.15	0.00	−0.09	−0.09
	$\widetilde{w}_1$	0.92	0.75	0.21	−0.20	0.00	−0.12	−0.18
	$\widetilde{w}_2$	0.95	0.89	0.19	−0.11	0.00	−0.13	−0.13
	$\widetilde{w}_3$	0.99	0.96	0.18	−0.06	−0.02	−0.14	−0.10
	$\widetilde{w}_4$	1.12	0.79	0.06	−0.15	0.03	−0.12	0.04
	$\widetilde{w}_5$	1.09	0.91	−0.02	−0.08	0.00	0.05	0.20
Standard deviation	Firms	0.88	1.28	1.77	0.95	0.86	2.15	2.56
	Portfolios	0.09	0.14	0.20	0.11	0.10	0.22	0.27
	$\widetilde{w}_1$	0.11	0.19	0.28	0.14	0.13	0.31	0.40
	$\widetilde{w}_2$	0.13	0.22	0.29	0.14	0.16	0.30	0.42
	$\widetilde{w}_3$	0.20	0.28	0.40	0.20	0.21	0.36	0.54
	$\widetilde{w}_4$	0.29	0.46	0.51	0.29	0.35	0.57	0.77
	$\widetilde{w}_5$	0.42	0.66	0.60	0.43	0.52	0.65	0.97
Panel B. Newey-West t-statistics								
Mean	Firms	2.93	1.86	1.64	1.46	1.33	1.61	1.33
	Portfolios	12.27	7.03	1.03	−1.51	0.00	−0.47	−0.32
	$\widetilde{w}_1$	8.69	4.24	0.85	−1.61	0.01	−0.41	−0.42
	$\widetilde{w}_2$	8.78	5.14	0.84	−0.97	−0.03	−0.53	−0.36
	$\widetilde{w}_3$	5.89	4.19	0.61	−0.34	−0.15	−0.51	−0.19
	$\widetilde{w}_4$	4.92	2.07	0.12	−0.64	0.08	−0.26	0.05
	$\widetilde{w}_5$	1.31	0.99	−0.01	−0.14	0.02	0.05	0.12
Fraction significant	Firms	0.64	0.48	0.22	0.17	0.12	0.19	0.13
	Portfolios	1.00	1.00	0.21	0.33	0.07	0.15	0.07
	$\widetilde{w}_1$	1.00	0.97	0.16	0.36	0.06	0.11	0.07
	$\widetilde{w}_2$	1.00	0.99	0.19	0.21	0.11	0.17	0.11
	$\widetilde{w}_3$	1.00	0.96	0.18	0.13	0.14	0.18	0.11
	$\widetilde{w}_4$	0.98	0.52	0.08	0.16	0.04	0.14	0.05
	$\widetilde{w}_5$	0.18	0.13	0.00	0.02	0.04	0.01	0.01

indicate that a massive 100% of the risk loadings are significant for the market and size factors when estimated on random portfolios. However, we are unable to obtain statistically significant risk loadings for the other factors, even with random portfolios.[7] This might explain why we do not find positive prices of risk for the value, momentum, liquidity, profitability, and investment factors.

Across horizons, we find that many portfolios have market and size risk loadings that are statistically significant up to a certain horizon. A massive 98% of the market risk loadings are significant at the sixteen- to 32-month horizon, while only 18% of the risk loadings are significant at the longest horizon that we consider. Similarly, we find that 96% of the size risk loadings are significant at the eight- to sixteen-month horizon, while only 52% and 13% of the risk loadings are significant at the sixteen- to 32-month horizon and the 32- to 64-month horizon, respectively. For the other factors, very few risk loadings are statistically significant across horizons. These results correspond to the pricing results because we only find significant prices of risks if the risk loadings are statistically different from zero. The reverse is not always true, since we do not find that all cases in which the majority of risk loadings are significant are associated with significant risk premium estimates. In particular, we only find the market factor to be priced up to sixteen months although we find most market risk loadings to be significant up to the horizon of 32 months.

We proceed by examining by how much the horizon-specific risk loadings differ from each other by looking at their cross-sectional correlations. This is important, because if the risk loadings are very different across horizons, then it is crucial to consider investment horizon in pricing tests. Table 2.6 shows that the correlation between the loadings estimated with non-decomposed factor returns and the shortest-horizon component ranges from 0.71 for the profitability factor to 0.84 for the investment factor, indicating that those risk loadings are closely connected. The correlations decrease as we compare loadings on factors with more distant horizons. For instance, the correlations between the raw risk loadings and the longest-horizon risk loadings

[7] We have tried the Vasicek (1973) shrinkage method to reduce the effect of estimation error in the risk loadings on our risk premium estimates. In untabulated results, we find that that the cross-sectional results are qualitatively similar when using Vasicek-corrected risk loadings.

Table 2.6. Cross-Sectional Correlations Between Risk Loadings

This table presents aggregate and horizon-specific cross-sectional Pearson correlations between risk loadings of several factors. The portfolio returns correspond to 1,000 random portfolios. Results are presented for all the risk factors of the Fama and French (2015) five-factor model, and the momentum and liquidity factors of the Carhart (1997) four-factor model augmented with the liquidity factor of Pastor and Stambaugh (2003). The factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. We apply the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the portfolio excess returns and risk factors. We exclude $7 \times (2^j - 1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. We then estimate full sample risk loadings on a horizon-by-horizon basis. We use risk loadings based on non-decomposed (Portfolios) and decomposed ($\widetilde{w}_1$ to $\widetilde{w}_5$) excess returns and risk factors. The sample period is from January 1968 to December 2015. We present average results based on 100 independent simulation runs.

	MKT					SMB				
	$\widetilde{w}_1$	$\widetilde{w}_2$	$\widetilde{w}_3$	$\widetilde{w}_4$	$\widetilde{w}_5$	$\widetilde{w}_1$	$\widetilde{w}_2$	$\widetilde{w}_3$	$\widetilde{w}_4$	$\widetilde{w}_5$
Portfolios	0.78	0.72	0.52	0.39	0.28	0.79	0.63	0.45	0.38	0.16
$\widetilde{w}_1$		0.46	0.10	0.05	0.01		0.34	0.10	0.07	0.01
$\widetilde{w}_2$			0.33	0.10	0.05			0.24	0.04	0.01
$\widetilde{w}_3$				0.39	0.12				0.42	0.04
$\widetilde{w}_4$					0.31					0.19
	HML					WML				
Portfolios	0.80	0.72	0.54	0.51	0.14	0.78	0.74	0.60	0.44	0.39
$\widetilde{w}_1$		0.42	0.16	0.14	0.04		0.49	0.20	0.14	0.11
$\widetilde{w}_2$			0.40	0.22	0.02			0.42	0.16	0.09
$\widetilde{w}_3$				0.43	0.03				0.42	0.22
$\widetilde{w}_4$					0.22					0.40
	LIQ					RMW				
Portfolios	0.78	0.69	0.47	0.19	0.24	0.71	0.75	0.57	0.20	0.13
$\widetilde{w}_1$		0.38	0.11	−0.01	0.07		0.31	0.06	0.03	0.00
$\widetilde{w}_2$			0.37	0.00	0.09			0.42	−0.01	0.00
$\widetilde{w}_3$				0.29	0.15				0.19	0.00
$\widetilde{w}_4$					0.23					0.27
	CMA									
Portfolios	0.84	0.73	0.48	0.19	0.26					
$\widetilde{w}_1$		0.43	0.17	0.01	0.12					
$\widetilde{w}_2$			0.41	0.04	0.12					
$\widetilde{w}_3$				0.32	0.15					
$\widetilde{w}_4$					0.27					

Table 2.7. Time Series R^2s

This table presents average R^2s from time series regressions of raw and decomposed excess portfolio returns on raw and decomposed risk factors, respectively, as well as the number of observations used in each time series regression (T). The returns are from 1,000 random portfolios. We use the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model augmented with the Pastor and Stambaugh (2003) traded liquidity factor, and the Fama and French (2015) five-factor model. We apply the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the portfolio excess returns and risk factors. We exclude $7 \times (2^j - 1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. We then estimate full sample risk loadings on a horizon-by-horizon basis. The sample period is from January 1968 to December 2015. We present average results based on 100 independent simulation runs.

	Portfolios	$\widetilde{w}_1$	$\widetilde{w}_2$	$\widetilde{w}_3$	$\widetilde{w}_4$	$\widetilde{w}_5$
CAPM	0.31	0.24	0.35	0.45	0.45	0.35
FF3	0.39	0.32	0.44	0.53	0.52	0.50
C4 + LIQ	0.40	0.33	0.46	0.54	0.55	0.56
FF5	0.40	0.32	0.45	0.54	0.55	0.56
T	576	569	555	527	471	359

range from 0.13 for the profitability factor to 0.39 for the momentum factor. We also find that risk loadings between adjacent components have positive correlations that roughly vary between 0.2 and 0.5, and that the risk loadings between non-adjacent components have correlations that are generally close to zero. In general, the correlations between loadings estimated at different horizons are rather low, indicating that horizon effects are present in the risk loadings. Overall, these results suggest that isolating fluctuations that correspond to a specific horizon is likely to result in different loadings on risk factors.

In Table 2.7, we report averages of the time series R^2s of all our models and across the specifications at different horizons. The R^2s based on non-decomposed returns and factors range from 0.31 for the CAPM to 0.40 for the Fama and French (2015) five-factor model. In general, and in line with the literature (Gençay, Selçuk, and Whitcher, 2003), the R^2s increase slightly as we move from the short-term horizon to the long-term horizon, indicating that the relation between portfolio returns and factors becomes marginally stronger over longer horizons. For instance, the R^2s corresponding to the multiple factor models increase from 0.32-0.33 at the shortest horizon to 0.50-0.56 at the longest horizon. The results for the CAPM are slightly different, because the corresponding R^2 increases from 0.24 at the shortest horizon to 0.45 at intermediate horizons, while the R^2 corresponding to the very long-horizon is slightly lower at 0.35. But although the R^2s generally increase with horizon, the pricing results do not become stronger in the long term.

Overall, the results suggest that horizon effects are present in the estimation of risk loadings. Across both factors and horizons, there is substantial variation in the magnitude and significance levels of the risk loadings. These effects are strong enough to pinpoint specific horizons at which certain risk factors manifest themselves. In particular, market risk loadings can be estimated precisely up to 32 months, and size risk loadings can be estimated precisely up to roughly sixteen months. These results correspond roughly to the horizon effects that are present in the horizon-specific market prices of risk discussed above.

2.6 Conclusion

This paper is motivated by recent theoretical work (e.g., Beber, Driessen, and Tuijp, 2012; Brennan and Zhang, 2016) that shows that if investor horizons are stochastic or heterogeneous, the pricing of risk is no longer horizon-invariant as in the CAPM, but, instead, may exhibit significant horizon effects. In this paper, we study whether risk premia associated with the fluctuations in a number of risk factors from several popular multi-factor asset pricing models vary across different horizons. We use wavelet analysis to decompose the returns on our test assets and on seven different risk factors into five components associated with fluctuations at very high frequencies (horizon of two to four months), intermediate frequencies (horizons of four to eight, eight to sixteen, and sixteen to 32 months), and very low frequencies (horizons of 32 to 64 months). We find that the market and size factors are priced when using non-decomposed monthly returns. Across horizons, we find that they are priced at intermediate horizons up to sixteen months, and that there is little evidence that the value, momentum, liquidity, profitability, and investment factors are priced at any of the horizons we consider. Our results have important implications for our understanding of what types of risk investors want to be compensated for in the cross-section of stock returns. Future research should shed more light on why different risk factors are priced at different horizons.

Appendices

2.A Robustness Checks

This appendix contains additional diagnostics and robustness checks for the cross-sectional Fama and MacBeth (1973) results reported in Table 2.4. In particular, we present Shanken (1992) t-statistics, and we re-estimate the cross-sectional results using the Haar filter and the discrete wavelet transform.

Shanken Correction

We calculate Shanken (1992) t-statistics as one might worry that estimation error in the risk loadings biases our risk premium estimates. This problem is referred to as the errors-in-variables (EIV) problem. Table 2.A.1 shows that, at the firm- and portfolio-level, the Shanken (1992) t-statistics are around 2.0 for both the market and size factors, and below conventional significance levels for the other factors. Thus, the results based on non-decomposed returns are robust to the choice of t-statistics.

The pricing results across horizons are also similar when using Shanken (1992) t-statistics, except for the shortest horizon. In particular, the Newey and West (1987) t-statistics indicate that the market and size factors have significant prices of risk at the shortest horizon, while the Shanken (1992) t-statistics are below conventional significance levels. This sensitivity to the way the t-statistics are computed is consistent across all the models. We conclude that our main conclusions remain unchanged, but that the short-term pricing results of the market and size factors are sensitive to the choice of t-statistics.

Haar filter

We also use the maximum overlap discrete wavelet transform (MODWT) with the Haar filter instead of the Daubechies (1992) least asymmetric filter. In addition to the frequently used Daubechies (1992) filter (e.g., Gençay, Selçuk, and Whitcher, 2003), the literature also frequently employs the Haar filter (e.g., Bandi and Tamoni, 2017). An advantage of this filter that is especially relevant to our setting is that less observations need to be dropped as a result of boundary conditions, such that the risk loadings, and in particular those based on the long-term components, can be more precisely estimated. Instead of dropping, for instance, $7 \times (2^5 - 1) = 217$ observations in the fifth component when using the LA8 filter, the Haar filter requires us to drop only $(2^5 - 1) = 31$ observations in order to remove any effect from boundary conditions. The results presented in Table 2.A.2 show that the results are very similar with this alternative wavelet filter.

Discrete Wavelet Transform

We also try the discrete wavelet transform (DWT) instead of the maximum overlap discrete wavelet transform (MODWT). The main reason we try this alternative transform is that the DWT is non-redundant, such that the components that are used to estimate the risk loadings are not necessarily (highly) auto-correlated. Autocorrelation is problematic because it might lead to estimation errors in the risk loadings. The fact that the components are autocorrelated when using the MODWT explains why we use Newey and West (1987) instead of regular t-statistics in Table 2.5. However, the DWT also has some major drawbacks because it is not invariant to circular shifting of the time series, and it is asymptotically less efficient than the MODWT. Nevertheless, the results in Table 2.A.3 show that the conclusions remain similar with this alternative transform.

Table 2.A.1. Monthly Cross-Sectional Fama-MacBeth Regressions with Shanken Correction

This table presents results from cross-sectional Fama and MacBeth (1973) regressions based on raw and horizon-specific risk loadings. The portfolio returns are from 1,000 random portfolios. We use the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model augmented with the Pastor and Stambaugh (2003) traded liquidity factor, and the Fama and French (2015) five-factor model. The factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. We apply the maximum overlap discrete wavelet transform (MODWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the portfolio excess returns and risk factors. We exclude $7 \times (2^j - 1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. We obtain full sample risk loadings on a horizon-by-horizon basis and run cross-sectional Fama and MacBeth (1973) regressions. We report Shanken (1992)-corrected *t*-statistics. Results are presented for risk loadings that correspond to aggregate risk loadings (Firms and Portf.), and horizon-by-horizon risk loadings ($\widetilde{w}_1$ to $\widetilde{w}_5$). The sample period is from January 1968 to December 2015. We present average results based on 100 independent simulation runs.

		CAPM	FF3			C4 + LIQ					FF5				
		MKT	MKT	SMB	HML	MKT	SMB	HML	WML	LIQ	MKT	SMB	HML	RMW	CMA
Shanken	Firms	2.49	2.25	1.85	−1.28	2.20	1.82	−1.20	0.48	−0.42	2.15	1.86	−1.24	−1.22	−0.71
t-statistics	Portf.	2.20	1.83	2.12	−0.85	1.72	2.09	−0.93	−0.66	−0.43	1.88	2.13	−0.80	−1.26	−0.57
	$\widetilde{w}_1$	1.35	1.24	1.36	−0.67	1.18	1.35	−0.63	−0.54	−0.20	1.17	1.28	−0.48	−1.32	−0.50
	$\widetilde{w}_2$	1.90	1.77	1.87	−0.69	1.87	1.87	−0.73	−0.18	−0.24	1.80	1.90	−0.70	−1.04	−0.70
	$\widetilde{w}_3$	2.00	1.96	2.16	−0.77	1.96	2.14	−0.85	−0.20	−0.49	1.92	2.12	−0.60	−1.30	−0.70
	$\widetilde{w}_4$	1.52	1.50	0.53	−0.98	1.40	0.60	−0.97	−0.69	−0.51	1.50	0.47	−0.87	−1.09	−0.60
	$\widetilde{w}_5$	1.29	1.18	0.98	−0.69	1.09	0.88	−0.63	0.15	−0.95	1.25	1.02	−0.81	−0.56	−0.62

Table 2.A.2. Monthly Cross-Sectional Fama-MacBeth Regressions with Haar Filter

This table presents results from cross-sectional Fama and MacBeth (1973) regressions based on raw and horizon-specific risk loadings. The portfolio returns are from 1,000 random portfolios. We use the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model augmented with the Pastor and Stambaugh (2003) traded liquidity factor, and the Fama and French (2015) five-factor model. The factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. We apply the maximum overlap discrete wavelet transform (DWT) based on the Haar wavelet filter to the portfolio excess returns and risk factors. We exclude $2^j - 1$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. We obtain full sample risk loadings on a horizon-by-horizon basis and run cross-sectional Fama and MacBeth (1973) regressions. We report annualized risk premium estimates based on normalized risk loadings, corresponding Fama and MacBeth (1973) t-statistics with Newey and West (1987) adjustment, and average cross-sectional $\boldsymbol{R}^2$s. Results are presented for risk loadings that correspond to aggregate risk loadings (Portf.), and horizon-by-horizon risk loadings ($\widetilde{w}_1$ to $\widetilde{w}_5$). The sample period is from January 1968 to December 2015. We present average results based on 100 independent simulation runs.

		CAPM		FF3				C4 + LIQ						FF5					
		MKT	$\boldsymbol{R}^2$	MKT	SMB	HML	$\boldsymbol{R}^2$	MKT	SMB	HML	WML	LIQ	$\boldsymbol{R}^2$	MKT	SMB	HML	RMW	CMA	$\boldsymbol{R}^2$
Risk premia	Portf.	0.58	0.36	0.50	0.69	−0.27	1.03	0.44	0.67	−0.29	−0.23	−0.11	1.60	0.52	0.65	−0.31	−0.42	−0.22	1.66
Normalized	$\widetilde{w}_1$	0.38	0.34	0.37	0.53	−0.21	0.97	0.35	0.52	−0.20	−0.16	−0.03	1.55	0.35	0.49	−0.17	−0.49	−0.23	1.57
	$\widetilde{w}_2$	0.58	0.34	0.58	0.65	−0.25	0.98	0.55	0.65	−0.26	−0.09	−0.07	1.55	0.58	0.62	−0.29	−0.41	−0.28	1.59
	$\widetilde{w}_3$	0.61	0.32	0.63	0.63	−0.26	0.92	0.59	0.62	−0.28	−0.11	−0.15	1.47	0.60	0.60	−0.29	−0.44	−0.24	1.51
	$\widetilde{w}_4$	0.51	0.30	0.60	0.38	−0.28	0.88	0.53	0.42	−0.27	−0.33	−0.25	1.42	0.59	0.37	−0.29	−0.43	−0.20	1.45
	$\widetilde{w}_5$	0.28	0.29	0.27	0.57	−0.21	0.85	0.25	0.50	−0.21	−0.40	−0.24	1.40	0.30	0.57	−0.24	−0.14	−0.05	1.41
Newey-West	Portf.	1.99		1.68	2.24	−0.81		1.61	2.19	−0.90	−0.57	−0.48		1.74	2.28	−0.78	−1.14	−0.69	
t-statistics	$\widetilde{w}_1$	2.23		2.08	2.33	−0.95		2.03	2.28	−0.89	−0.71	−0.15		1.93	2.28	−0.68	−1.93	−0.90	
	$\widetilde{w}_2$	2.78		2.69	2.46	−1.05		2.78	2.44	−1.12	−0.32	−0.49		2.81	2.57	−1.03	−1.44	−1.25	
	$\widetilde{w}_3$	1.94		1.72	2.21	−0.85		1.74	2.18	−0.94	−0.32	−0.83		1.77	2.29	−0.75	−1.12	−0.77	
	$\widetilde{w}_4$	0.98		1.00	0.81	−0.50		0.94	0.91	−0.47	−0.46	−0.64		1.00	0.78	−0.43	−0.69	−0.32	
	$\widetilde{w}_5$	0.52		0.48	1.04	−0.33		0.43	0.93	−0.32	−0.53	−0.46		0.48	1.03	−0.34	−0.21	−0.06	

Table 2.A.3. Monthly Cross-Sectional Fama-MacBeth Regressions with DWT

This table presents results from cross-sectional Fama and MacBeth (1973) regressions based on raw and horizon-specific risk loadings. The portfolio returns are from 1,000 random portfolios. We use the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model augmented with the Pastor and Stambaugh (2003) traded liquidity factor, and the Fama and French (2015) five-factor model. The factors used are the market (MKT), size (SMB), value (HML), momentum (WML), liquidity (LIQ), profitability (RMW), and investment (CMA) factors. We apply the discrete wavelet transform (DWT) based on the least asymmetric Daubechies (1992) wavelet filter with eight lags (LA8) to the portfolio excess returns and risk factors. We exclude $7 \times (2^j - 1)$ observations at the beginning of the resulting time series to remove any effect of boundary conditions. In total we extract five components. We obtain full sample risk loadings on a horizon-by-horizon basis and run cross-sectional Fama and MacBeth (1973) regressions. We report annualized risk premium estimates based on non-normalized and normalized risk loadings, corresponding Fama and MacBeth (1973) t-statistics with Newey and West (1987) adjustment, and average cross-sectional R^2s. Results are presented for risk loadings that correspond to aggregate risk loadings (Portf.), and horizon-by-horizon risk loadings ($\widetilde{w}_1$ to $\widetilde{w}_5$). The sample period is from January 1968 to December 2015. We present average results based on 100 independent simulation runs.

		CAPM		FF3				C4 + LIQ						FF5					
		MKT	R^2	MKT	SMB	HML	R^2	MKT	SMB	HML	WML	LIQ	R^2	MKT	SMB	HML	RMW	CMA	R^2
Risk premia	Portf.	0.58	0.36	0.50	0.69	−0.27	1.03	0.44	0.67	−0.29	−0.23	−0.11	1.60	0.52	0.65	−0.31	−0.42	−0.22	1.66
Normalized	$\widetilde{w}_1$	0.35	0.33	0.34	0.39	−0.20	0.94	0.31	0.39	−0.21	−0.17	−0.05	1.51	0.33	0.36	−0.18	−0.42	−0.25	1.53
	$\widetilde{w}_2$	0.36	0.30	0.37	0.51	−0.15	0.90	0.38	0.53	−0.16	−0.06	−0.03	1.46	0.38	0.54	−0.18	−0.35	−0.10	1.47
	$\widetilde{w}_3$	0.49	0.30	0.65	0.58	−0.24	0.87	0.63	0.61	−0.23	−0.06	−0.15	1.41	0.58	0.53	−0.26	−0.32	−0.30	1.43
	$\widetilde{w}_4$	0.18	0.28	0.21	0.08	−0.15	0.83	0.26	0.10	−0.18	−0.26	−0.09	1.36	0.29	0.11	−0.29	−0.08	−0.17	1.37
Newey-West	Portf.	1.99		1.68	2.24	−0.81		1.61	2.19	−0.90	−0.57	−0.48		1.74	2.28	−0.78	−1.14	−0.69	
t-statistics	$\widetilde{w}_1$	2.15		1.96	1.85	−0.94		1.83	1.84	−0.95	−0.78	−0.39		1.81	1.81	−0.70	−1.73	−1.01	
	$\widetilde{w}_2$	2.76		2.84	2.26	−0.83		2.98	2.26	−0.93	−0.37	−0.22		2.93	2.30	−1.01	−1.46	−0.54	
	$\widetilde{w}_3$	1.73		1.70	1.98	−0.86		1.78	1.99	−0.88	−0.18	−0.78		1.75	2.07	−0.78	−1.03	−1.02	
	$\widetilde{w}_4$	0.42		0.45	0.18	−0.28		0.54	0.22	−0.30	−0.44	−0.20		0.55	0.23	−0.34	−0.13	−0.24	

Chapter 3

Using Factor Models to Compute Costs of Equity Capital*

3.1 Introduction

The asset pricing literature has put forward a large number of factors and characteristics that appear to explain the cross-section of stock returns (Harvey, Liu, and Zhu (2016) document 315 such variables). Building on this body of research, a variety of asset pricing models have been proposed. These models have important practical applications; for example, they can be used by CFOs to estimate the cost of equity capital. Indeed, since these models are actually used, they fulfill an important function in both corporate finance and investments.[1] However, there is scant evidence on whether or not asset pricing models provide reliable estimates of costs of equity capital.

In this paper, I investigate three important issues in such applications of asset pricing models. First, I examine the importance of model selection. Specifically, I investigate to what extent the cost of equity, or expected return, estimates produced by five popular asset pricing models differ in the time series and the cross-section. If models broadly agree on expected returns, then the choice of using the CAPM or another asset pricing model does not affect corporate and investment decisions. If there is substantial disagreement between asset pricing models, however, then the choice of model matters. Second, and building on Fama and French (1997) and

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[1] Graham and Harvey (2001) report that 73.5% of the surveyed CFOs use the CAPM; 34.3% of the respondents that use the CAPM also include additional risk factors.

Ferson and Locke (1998), I examine the standard errors with which expected returns are estimated and compare them across models. This is relevant because imprecision in expected return estimates decreases the usefulness of models in applications where precise values are crucial, such as valuation and corporate capital budgeting. Third, I examine the out-of-sample forecasting performance of the asset pricing models. This is important because corporate financial and investment decisions rely on models to produce accurate benchmarks of future returns.

I consider the following five popular asset pricing models: (1) the CAPM, (2) the Fama and French (1993) three-factor model, (3) the Carhart (1997) four-factor model, (4) the Fama and French (2015) five-factor model, and (5) the Hou, Xue, and Zhang (2015) four-factor model. While many more asset pricing models have been proposed, the focus of this paper is on providing an in-depth analysis of the expected return estimates derived from five key models, not on comparing all the asset pricing models.[2] I use these models to estimate expected returns for individual firms and industries from 1977 to 2013. I mimic the usage of these models in practice and compute expected returns following the instructions in widely-used corporate finance textbooks.[3] In particular, I use full sample and rolling window regressions to estimate risk loadings, and average factor realizations to estimate risk premia. I calculate expected returns by multiplying the risk loadings by the corresponding risk premia and, for multi-factor models, by taking the sum of the resulting products.

In my first analysis, I compute "model disagreement" for each firm and industry as the range and standard deviation of the five expected return estimates each month. I show that there is large disagreement between the models about expected returns. Specifically, the time series average of the annualized mean (median) range between the rolling window estimates is 19.24% (16.81%) for individual firms and 7.01% (6.42%) for industries. Thus, the choice of model is important, because it

[2]The choice of models is consistent with model comparisons in the literature (e.g., Barillas and Shanken, 2015). Some other well-known models include the BARRA and BIRR models, which are based on Rosenberg and McKibben (1973), Rosenberg (1974), Ross (1976a), and Ross (1976b). These commercially very successful models require estimation of many parameters and therefore the expected return estimates are likely to be associated with even greater standard errors than those from the five models considered in this paper.

[3]See Levi and Welch (2017, p.428) for an overview on the prescriptions for computing the cost of equity capital given by three common corporate finance textbooks.

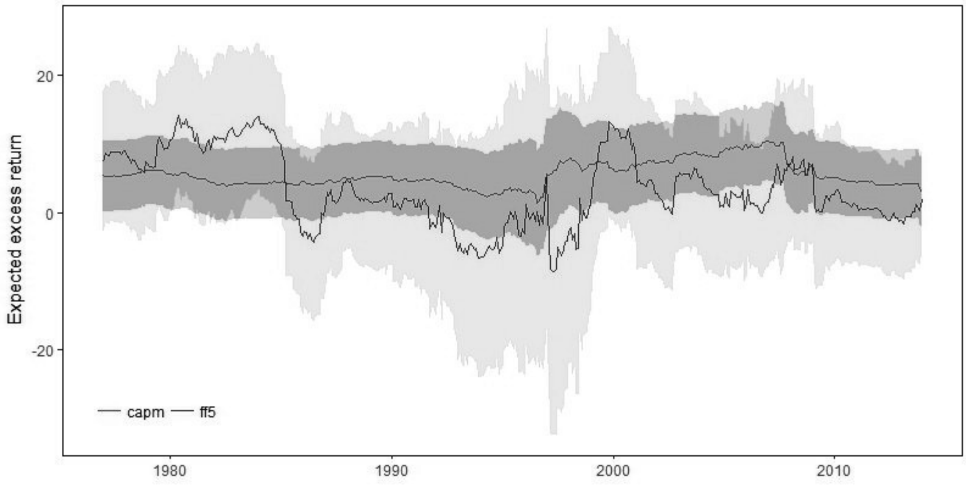
is likely to often lead to substantially different project valuations and investment decisions.

In my second analysis, I revisit the work by Fama and French (1997), who establish that the expected return estimates produced by the CAPM and the Fama and French (1993) three-factor model are estimated very imprecisely, thereby afflicting their practical application. In line with their approach, I examine the standard errors around the expected return point estimates produced by the different models. I show that these standard errors are very large and that they increase markedly when additional factors are included in the model. For individual firms, the average standard error ranges from more than 4% per year for the CAPM to around 13% per year for the Hou, Xue, and Zhang (2015) four-factor model and the Fama and French (2015) five-factor model. For industries, the average standard errors of expected returns are also large, but considerably smaller than those for individual firms. They range from almost 3% per year for the CAPM to over 4% per year for the Hou, Xue, and Zhang (2015) four-factor model and the Fama and French (2015) five-factor model. Standard errors are higher during the Internet Bubble and the Global Financial Crisis, which suggests that the practical use of those models is more dubious during volatile periods. I also decompose the part of the estimation error that stems from estimation error in the risk loadings and the risk premia. I confirm the results of Fama and French (1997) and Ferson and Locke (1998) that the estimation error in CAPM expected returns are mainly driven by estimation error in the risk premia. For multi-factor models, the risk premia are also estimated imprecisely, but the risk loadings are so imprecise such that the associated estimation errors contribute mostly to the expected returns estimation errors.

To illustrate the behavior of the expected return estimates over time, the extent to which models disagree about expected returns, and how enormous the standard errors are, I plot two time series of monthly expected return estimates for IBM in Figure 3.1. The expected returns are from the CAPM and the Fama and French (2015) five-factor model. The expected return estimates, and especially those produced by the Fama and French (2015) five-factor model, exhibit considerable variability, which is likely

Figure 3.1. Time Series of Expected Return on IBM

This figure shows annualized expected returns estimates plus and minus one standard deviation from 1977 to 2013 for IBM. The models used to estimate the expected return are the CAPM (red line and confidence bound) and the Fama and French (2015) five-factor model (blue line and confidence bound). Details about the estimation procedure are provided in Section 3.5.



to be unattractive for a CFO interested in computing the cost of equity capital. The annualized expected returns fluctuate between 1.44% and 10.44% for the CAPM and between −8.50% and 14.13% for the Fama and French (2015) five-factor model. The difference between the estimates is 5.03% on average, which is large by itself. In some periods the expected return estimates produced by the Fama and French (2015) five-factor model are negative, which is also unattractive in calculations of the cost of equity capital. Moreover, the expected returns are estimated with wide uncertainty. The time series average standard error is 2.50% per year for the CAPM and 5.45% per year for the Fama and French (2015) five-factor model, leading to wide confidence bounds for those estimates.

Given the high degree of uncertainty involved in the estimation of expected returns, one might question the applicability of asset pricing models for CFOs and investors. Yet, although the estimation errors are large, the point estimates might still be informative about "true" expected returns. In my third analysis, I examine the out-of-sample forecasting performance of the expected return estimates. Since the slope coefficients are way below one, the predictions are far from perfect. Nevertheless, the expected return estimates produced by the Fama and French (1993) model are informative about the one-month-ahead realized returns of firms, and those produced by the Carhart (1997) and Hou, Xue, and Zhang (2015) models are informative about one-month-ahead realized returns of industries. The models also have weak predictive ability for one-year-ahead returns, but not for five-year-ahead returns. This last result is worrying, because CFOs would need models that have long-term forecasting ability for capital budgeting and long-horizon decision making.

Importantly, I find that the predictive power of the expected return estimates produced by the different models depends on their standard errors. For individual firms, I find that the relatively precise expected return estimates produced by all models are positively related to subsequent realized returns, and that three out of five are statistically significant. This relation holds for one-year-ahead forecasts (three positive and significant) and five-year-ahead forecasts (two positive and significant). For medium and large levels of estimation error, I find that the predictive power largely disappears across all forecasting horizons. Overall, the results show that estimation error is related to the informativeness of the point estimates. As a remedy for the large standard errors of the firm cost of equity estimates, CFOs might be tempted to employ the industry cost of equity as the firm cost of equity.[4] However, and consistent with Levi and Welch (2014) and Levi and Welch (2017), I find that using industry estimates does not result in better forecasts at any horizon.

My results have several implications. First, the choice of model does have a significant impact on corporate finance and investment decisions. The models produce estimates of expected returns that differ greatly in economic terms, thereby increasing uncertainty about a security's "true" expected return. Second, the standard errors with which expected returns are estimated might be another criterion to judge whether to use a particular model. Since risk loadings and premia are estimated with large standard errors, the expected return estimates are extremely imprecise. The

[4]Corporate finance textbooks recommend using industry betas. For instance, Koller, Goedhart, and Wessels (2010) write that "To improve the precision of beta estimation, use industry, rather than company-specific betas. Companies in the same industry face similar operating risks, so they should have similar operating betas. As long as estimation errors across companies are uncorrelated, overestimates and underestimates of individual betas will tend to cancel, and an industry median (or average) beta will produce a superior estimate."

standard errors are positively related to the number of factors in an asset pricing model, which suggests that there is a trade-off between the relatively large standard errors of multi-factor models and the benefits of improved pricing ability that additional factors provide. Third, the results indicate that practitioners should question the use of asset pricing models to compute expected returns. This is especially true if the estimates are imprecise, because imprecisely estimated expected returns do not tend to align with realized returns.

This paper contributes to two different strands of the literature. First, there is a stream of literature on using asset pricing models to estimate the cost of equity and expected returns. Fama and French (1997) consider the CAPM and the Fama and French (1993) three-factor model. They show that both model choice and estimation error result in massive uncertainty about expected return estimates for industries. However, they do not consider firms or projects for which expected returns are surely estimated even more imprecisely. Levi and Welch (2014) build on this work and conclude that the predictive ability of the CAPM and the Fama and French (1993) model is basically useless for long-term capital budgeting purposes both on an a priori and ex post basis. They argue that risk loadings should be shrunk to the point where there is little cross-sectional dispersion left. They recommend to not adjust projects for risk but to use one constant expected return estimate for all projects. To obtain forward-looking estimates, Levi and Welch (2017) also argue that risk loadings need to be shrunk aggressively. My paper is different and contributes to this literature because I focus on model *disagreement* by comparing five popular asset pricing models and study the extent to which they produce different expected return estimates in the cross-section and over time, both from an economic and statistical perspective. Moreover, I examine the interplay between estimation error and out-of-sample forecasting performance, while previously these concepts have been evaluated in isolation.

Second, a large number of factors and asset pricing models have been proposed in another stream of the literature. Harvey, Liu, and Zhu (2016) list 315 factors and characteristics that have been demonstrated to relate to the cross-section of expected stock returns. It is not clear, however, which variables should be used in models to compute the cost of equity capital. For instance, Lewellen, Nagel, and Shanken (2010) argue that it seems very easy to construct models that do well in explaining the cross-section of stock returns due to the low hurdle rates used for claiming success. Cochrane (2011) questions whether all the proposed factors provide independent information about expected returns. Many researchers have started to navigate through the zoo of factors and to evaluate the performance of factor models (Simin, 2008; Kapadia and Paye, 2014; Barillas and Shanken, 2015). Linnainmaa and Roberts (2016) show that many of the anomalies used to motivate asset pricing models are spurious. There is also evidence showing that characteristics provide explanatory power for the cross-sectional variation in expected stock returns (Daniel and Titman, 1997; Lewellen, 2015; Freyberger, Neuhier, and Weber, 2017; Yan and Zheng, 2017). I contribute to this literature by evaluating the usefulness of five (out of many) asset pricing models that are available in computing the cost of equity capital.

3.2 Models, Method, and Data

In this paper I examine expected returns from linear factor models. The focus is on expected returns estimated as described in typical corporate finance textbooks. In this section, I describe the five models that I consider in this paper, the method that I use to estimate expected returns, and the data.

3.2.1 Asset Pricing Models

The CAPM, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model are classic models that are frequently used by academic researchers to evaluate the performance of financial assets (e.g., Goyal, 2012). Although there is much empirical evidence showing that the CAPM does a poor job in explaining the cross-section of stock returns, it is still heavily used for making investment decisions (Graham and Harvey, 2001). The Fama and French (1993) model does a much better job, but a large number of anomalies cannot be explained by this model (Fama and French, 2016). The Carhart (1997) model, in which a momentum factor is added to the Fama and French (1993) model to account for the momentum anomaly, is also widely used. There is evidence that the Fama and French (1993) and Carhart (1997) models are also used by CFOs (Graham and Harvey, 2001).

Fama and French (2015) and Hou, Xue, and Zhang (2015) propose new asset pricing models that seem to explain many asset pricing anomalies. Fama and French (2015) add profitability and investment factors to the three factors in Fama and French (1993). Hou, Xue, and Zhang (2015) propose a model that includes market, size, profitability, and investment factors. Both studies show that their models explain a substantial number of asset pricing anomalies that are not picked up by the three classical models. Realizing the similarity between the factors that are included in the Fama and French (2015) and Hou, Xue, and Zhang (2015) models, Hou, Xue, and Zhang (2017) compare how both models perform and present evidence suggesting that the Hou, Xue, and Zhang (2015) model outperforms the Fama and French (2015) model in explaining a long list of asset pricing anomalies.

However, the model with the best in-sample fit is not necessarily the most appropriate one for computing the cost of equity capital. The cost of capital requires forward-looking risk premia and risk loadings (Levi and Welch, 2017), and these parameters might be hard to estimate for models that have a relatively good in-sample fit as they generally contain relatively many factors.

3.2.2 Method

I use the five asset pricing models to construct unconditional and conditional expected returns. For the unconditional returns, the risk loadings are assumed to be constant over time, while for the conditional expected returns I allow for time variation in the risk loadings. Suppose there are K risk factors. In the unconditional model, the expected excess return on security i is:

$$E(R_i) = \hat{\beta}_i' \hat{E}(F), \tag{3.1}$$

where $E(R_i)$ is the security's expected excess return, $\hat{\beta}_i$ denotes a $K \times 1$ vector of unconditional risk loadings, and $\hat{E}(F)$ denotes a $K \times 1$ vector of expected factor risk premia, assumed to be constant over time. The risk loadings can be determined by the full sample time series regression, as follows:

$$R_{i,t} = \alpha_i + \beta_i' F_t + \epsilon_{i,t}, \tag{3.2}$$

where $R_{i,t}$ is a $T \times 1$ vector of realized excess returns, α_i is the regression intercept, and $\epsilon_{i,t}$ is a $T \times 1$ vector of unconditional error terms with $E(\epsilon_{i,t}) = 0$, $cov(\epsilon_{i,t}, \epsilon_{i,s}) = 0$ for $t \neq s$, and $cov(F_t, \epsilon_{i,t}) = 0$. The time series averages of the factor realizations are used as the factor risk premia in equation (3.1).

I also consider a conditional model in which I estimate risk loadings with rolling window regressions. In this setting, expected returns are estimated by:

$$E_t(R_{i,t+1}) = \hat{\beta}_{i,t}' \hat{E}_t(F_{t+1}), t = \tau, \ldots, T, \tag{3.3}$$

where $E_t(R_{i,t+1})$ is an $(T - \tau) \times 1$ vector of expected excess returns, $\beta_{i,t}$ denotes a $(T - \tau) \times K$ vector of time-varying risk loadings, $\hat{E}_t(F_{t+1})$ is a $K \times 1$ vector of time-varying expected factor premia, and τ is the length of the estimation window of the risk loadings. The risk loadings are estimated using the time series regressions:

$$R_{i,t}(\tau) = \alpha_{i,t}(\tau) + \beta_{i,t}(\tau)' F_t(\tau) + \epsilon_{i,t}(\tau), t = \tau, \ldots, T, \tag{3.4}$$

such that the regression model is estimated using observations from time $t - \tau + 1$ to time t.

3.2.3 Data

I retrieve monthly stock return data from CRSP. The sample consists of ordinary common shares (share codes 10 and 11) that are listed on the NYSE, AMEX, and NASDAQ (exchange codes 1, 2, and 3) and covers the period from January 1972 to December 2013. I start in 1972 as the factor data employed by Hou, Xue, and Zhang (2015) are only available from this time. I require stock prices at the beginning of the month to be at least \$1. I require at least 60 return observations be available for the full sample regressions, and at least 24, 30, and 36 return observations be available for the three-, four- and five-year rolling window regressions, respectively. In addition, I require both full sample and rolling window risk loadings be available for comparative purposes. The final sample includes 12,807 unique firms and 1,679,566 firm-month observations. I retrieve data on returns for 48 industries and the risk-free rate from Kenneth French's Data Library.[5]

In Appendix 3.A, I provide an overview of all the factors included in the five models. I do not re-construct the factors in the models, but obtain them from the authors of the corresponding papers.[6] Since the Data Library is publicly available and the Hou, Xue, and Zhang (2015) factors are available from the authors upon request, it would be easy for a practitioner to acquire and use the models that I evaluate. Appendix 3.B provides details on how the factors are constructed.

3.3 Estimating Factor Risk Premia

One could take multiple approaches to estimate expected factor risk premia. I follow Fama and French (1997) and Levi and Welch (2014) and use arithmetic averages of the factor realizations as the expected risk premium estimates. I use prevailing averages that are based on information in real time in out-of-sample tests, thereby realistically reflecting what a practitioner could know when performing valuations or making investment decisions. The prevailing averages are calculated over the common sample period (which begins in January 1972) to ensure a fair comparison of the five models. My results are similar when I use prevailing averages over the entire period for which data are available (i.e., the start of the sample varies across factors).

I also estimate the risk premia by calculating the full sample (ex post) arithmetic average factor realizations. Although these ex post estimates contain more information about the true factor risk premia by the law of large numbers, it is based on data that are not available in real time. I also estimate risk premia using geometric averages, which might be preferred because they incorporate compounding effects. Following the evidence in Goyal and Welch (2008) showing that predictive models of the equity risk premium perform poorly, and the evidence in Simin (2008) suggesting

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[6] I thank Kenneth French for making his factors available on his Data Library. I also thank Kewei Hou for making the Hou, Xue, and Zhang (2015) factors available.

that conditional versions of asset pricing models provide higher forecast errors than unconditional models, I do not use instrumental variables to proxy for time variation in risk premia.[7]

Table 3.1 presents summary statistics for the annualized risk premium estimates of the factors used in the five models over both the full and common sample period. Factors from different models that are defined differently but that are supposed to capture the same underlying risk, such as market, size, profitability, and investment risk, are grouped together. Panel A shows that the risk premia for the factors differ markedly in magnitude. The arithmetic (geometric) average factor realization over the common sample period ranges from 2.41% (1.84%) per year for the Fama and French (1993) size factor to 8.53% (7.52%) per year for the Carhart (1997) momentum factor.

The factors that have the most time-varying realizations are the market factors of the CAPM and the Hou, Xue, and Zhang (2015) four-factor model, and the momentum factor of Carhart (1997), which is reflected in standard errors of over 2% per year. Panel A of Table 3.1 also presents the standard deviation of the average factor realizations on a five-year rolling window, which provides information on the stability of the factor realizations over time. The realizations of the momentum factor vary the most over the common sample period, followed by the realizations of the size and market factors. Overall, the findings show that factor realizations vary over time, which results in estimation error in the factor risk premia.

Panel B of Table 3.1 displays time series correlations between factor returns. Not surprisingly, factors that are supposed to capture similar sorts of risks have high correlations. The correlation between the market factors from the CAPM and Hou, Xue, and Zhang (2015), and between the size factors from Fama and French (1993), Fama and French (2015), and Hou, Xue, and Zhang (2015) are all close to 1. In addition, both the profitability and investment factors of Fama and French (2015) and Hou, Xue, and Zhang (2015) have positive time series correlations, with

[7] Alternatively, one could use Fama and MacBeth (1973) cross-sectional regressions (e.g., Lewellen, 2015) or Bayesian approaches (e.g., Kapadia and Paye, 2014) to estimate factor risk premia. These approaches, however, are econometrically demanding and not considered to be standard in corporate finance applications.

Table 3.1. Risk Premia

This table presents statistics on the monthly realizations of the factors used in the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor, and the Hou, Xue, and Zhang (2015) four-factor model. The factor abbreviations are explained in Appendix 3.A and the factor construction is explained in Appendix 3.B. The table reports for each factor the annualized arithmetic average (Arith), the annualized geometric average (Geo), the annualized standard error of the risk premium estimate (SE), and the time series standard deviation of the factor realizations on a five year rolling window (SD). The left-hand side reports statistics for the full sample period. The starting date is indicated in the second column, and the ending date is the same for all factors: December 2013. The right-hand side reports statistics that correspond to the period 1972-2013, which is the period in which data is available for all the risk factors. The numbers are in percentages. Panel B shows the Pearson correlation coefficients between the factor realizations from January 1972 to December 2013.

Panel A: Summary statistics factor realizations

	Full sample period					Common sample period (1972-2013)			
Factor	Start	Arith	Geo	SE	SD	Arith	Geo	SE	SD
MKT	1926-07	7.79	6.20	2.00	0.62	6.32	5.14	2.46	0.49
MKT (HXZ4)	1972-01	6.17	4.99	2.47	0.47	6.17	4.99	2.47	0.47
SMB	1926-07	2.79	2.21	1.20	0.53	2.41	1.84	1.67	0.48
SMB (FF5)	1963-07	3.46	2.94	1.50	0.55	2.81	2.27	1.64	0.52
SMB (HXZ4)	1972-01	3.70	3.16	1.68	0.51	3.70	3.16	1.68	0.51
HML	1926-07	4.79	4.16	1.30	0.39	4.75	4.29	1.61	0.40
MOM	1927-01	8.24	6.90	1.77	0.49	8.53	7.52	2.39	0.54
PROF (FF5)	1963-07	3.04	2.80	1.04	0.28	3.44	3.18	1.20	0.28
PROF (HXZ4)	1972-01	6.78	6.56	1.40	0.30	6.78	6.56	1.40	0.30
INV (FF5)	1963-07	3.99	3.82	0.98	0.29	4.45	4.30	1.05	0.30
INV (HXZ4)	1972-01	5.32	5.24	1.00	0.25	5.32	5.24	1.00	0.25

Panel B: Pearson correlations factor realizations

	MKT (HXZ4)	SMB	SMB (FF5)	SMB (HXZ4)	HML	MOM	PROF (FF5)	PROF (HXZ4)	INV (FF5)	INV (HXZ4)
MKT	1.00	0.28	0.25	0.25	−0.32	−0.14	−0.23	−0.18	−0.39	−0.36
MKT (HXZ4)		0.28	0.25	0.25	−0.32	−0.14	−0.24	−0.19	−0.39	−0.37
SMB			0.99	0.95	−0.23	−0.01	−0.44	−0.39	−0.12	−0.23
SMB (FF5)				0.98	−0.11	−0.03	−0.39	−0.38	−0.05	−0.15
SMB (HXZ4)					−0.07	0.01	−0.38	−0.31	−0.01	−0.12
HML						−0.15	0.15	−0.09	0.70	0.69
MOM							0.09	0.50	0.02	0.04
PROF (FF5)								0.67	−0.03	0.10
PROF (HXZ4)									−0.09	0.06
INV (FF5)										0.90

coefficients of 0.67 and 0.90, respectively.

More importantly, Panel B of Table 3.1 also presents several high positive and negative correlation coefficients between factors that are not necessarily reflecting similar sources of risk. For instance, the size and profitability factors are negatively correlated (the correlations range between −0.31 and −0.44), the investment factors and the value factor are positively correlated (the correlation coefficients are 0.69 and 0.70), and the momentum factor is positively correlated with the Hou, Xue, and Zhang (2015) profitability factor (the correlation coefficient is 0.50). The high correlations might result in expected return estimates that are positively correlated in the cross-section and time series. For instance, even though the Carhart (1997) model is the only model that includes a momentum factor, it may still generate expected returns that are similar to the ones generated by the Hou, Xue, and Zhang (2015) model due to the positive correlation between the momentum factor and the profitability factor. As such, high correlations between factors are likely to alleviate the problem of model selection.

3.4 Estimating Risk Loadings

As for factor risk premia, one could adopt a variety of approaches to estimate risk loadings. I follow Fama and French (1997) and Levi and Welch (2014) and estimate risk loadings for individual firms and industries by running full sample and rolling window regressions of monthly excess returns on monthly factor returns. For the rolling regressions, I use estimation windows with lengths of 36, 48, and 60 months. My results are qualitatively similar when I use the Vasicek (1973) shrinkage method to estimate the risk loadings.

Since the focus of this paper is on the practical application of factor models, I restrict the analysis to the methods suggested in common finance textbooks, although more econometrically demanding approaches to estimate risk loadings have recently been proposed that seem to outperform the classical approaches. For instance, Cohen, Polk, and Vuolteenaho (2009) recommend using risk loadings based on cash flow news, Chang, Christoffersen, Jacobs, and Vainberg (2011) recommend using forward-looking risk loadings implied from options, and Cosemans, Frehen, Schotman, and

Bauer (2015) recommend using a Bayesian approach to estimate forward-looking risk loadings. This literature, however, generally focuses on estimating risk loadings on the market factor, and provide limited guidance on estimating risk loadings on other factors. Moreover, Ghysels (1998) shows that models with time-varying risk loadings often produce larger pricing errors than models with constant risk loadings when the dynamics of the risk loadings are misspecified. This is particularly relevant in the setting of this paper, because even a CFO might not be able to determine the exact dynamics of the exposures to all relevant risk factors.

The focus of this section is on two problems in the estimation of risk loadings (see also Fama and French, 1997; Levi and Welch, 2017). First, I investigate the precision of the risk loading estimates by examining the magnitude of their estimation errors. Second, I study whether any time series variation in the risk loadings can be attributed to estimation error. Risk loadings could change because firms operate in dynamic environments in which they continually undertake new projects and abandon old ones, which might affect the risk profile of their businesses. It is for this reason that risk loadings are often estimated by using a rolling window or by making use of conditional variables. However, any observed time variation might also reflect estimation error. Full sample risk loadings do not capture any time-varying behavior, and their estimation errors will be misleading if the risk loadings are not constant.

I follow Fama and French (1997) to test whether the estimation errors in the full sample risk loadings are driven by their variation over time. Specifically, I decompose the observed time series variance of risk loadings into a part that reflects the true time series variance and a part that is attributable to estimation error:

$$\sigma^2(True) = \sigma^2(Observed) - \sigma^2(Est.Err.), \tag{3.5}$$

where $\sigma^2(Observed)$ represents the time series variance of risk loadings estimated on a rolling window, $\sigma^2(Est.Err.)$ represents the time series average estimation error in the risk loadings, and $\sigma^2(True)$ is assumed to reflect the true variance of the risk loadings implied by the standard errors. Intuitively, when there is time variation in the risk loadings, their variance should exceed the variance that can be attributed to estimation error. If not, the time variation in risk loadings could be solely due to estimation error, which implies that using rolling regressions to estimate the risk loadings might not be a correct approach. When the variance of the true risk loadings is estimated to be negative, I set $\sigma^2(True)$ to zero due to the non-negativity constraint of variances.

In Table 3.2, I report the time series averages of the mean and median full sample risk loadings, standard errors of both the full sample and rolling window risk loadings, and implied standard deviations of the true risk loadings. Panel A presents the results for firms, while Panel B presents the results for industries.

The risk loadings of firms are estimated with large errors. Panel A in Table 3.2 shows that the mean (median) standard error of the CAPM market risk loadings estimated on a full sample is 0.21 (0.18). The standard errors of the risk loadings on the market factor increase when it is estimated jointly with other factors in multi-factor models. For instance, the mean (median) standard error on the market factor in the Fama and French (1993) model is 0.23 (0.19). With a mean (median) standard error of 0.74 (0.61) across firms, risk loadings on the investment factor of Fama and French (2015) are most imprecisely estimated. Applying the common two standard deviation rule and given that the point estimate of this investment factor is 0.00, this means that the average firm has a full sample risk loading which could be anywhere between -1.48 and 1.48. The standard error of the Fama and French (2015) investment factor is almost four times larger than the standard error on the CAPM market factor. In fact, all average standard errors of the loadings on the factors from the other models are greater than the average standard error of the CAPM market risk loadings. The standard errors increase substantially when risk loadings are based on rolling window regressions. For instance, the time series average of the mean (median) error of the risk loading on the CAPM market factor is 0.39 (0.34) for firms. The results in Table 3.2 show that there is considerable variation across firms in the implied standard deviation of the true risk loadings. For instance, the average true variance of the risk loadings on the SMB and HML factors in the Fama and French (1993), Carhart (1997), and Fama and French (2015) models across firms are

Table 3.2. Risk Loadings

The table shows summary statistics for full sample and rolling window risk loadings. Full sample risk loadings are calculated if at least 60 observations are available over the entire simple period. Rolling risk loadings are based on a five year window, and I require at least 36 return observations to be available. The first two columns show the time series average of the mean and median full sample risk loadings on the risk factors used in the capital asset pricing model (CAPM), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). The factors are listed in Table 3.A.1. The third and fourth column report the average and median standard errors of the full sample risk loadings. The fifth and sixth column report time series averages of the mean and median standard errors of the rolling window risk loadings. The last two columns report the implied standard deviations of the true risk factors. Panel A shows the results for firms and Panel B shows the results for industries. The sample period is from January 1972 to December 2013.

Panel A: Firms

		Full sample risk loadings		Full sample standard error		Rolling window standard error		Implied sd of true risk loadings	
Model	Factor	Mean	Median	Mean	Median	Mean	Median	Mean	Median
CAPM	MKT	1.06	1.02	0.21	0.18	0.39	0.34	0.12	0.00
FF3	MKT	0.99	0.98	0.23	0.19	0.46	0.40	0.09	0.00
	SMB	0.78	0.70	0.33	0.27	0.68	0.58	0.14	0.00
	HML	0.29	0.38	0.36	0.29	0.73	0.63	0.17	0.00
C4	MKT	0.97	0.96	0.24	0.20	0.48	0.41	0.09	0.00
	SMB	0.78	0.70	0.33	0.27	0.70	0.60	0.14	0.00
	HML	0.26	0.36	0.36	0.30	0.76	0.65	0.17	0.00
	MOM	−0.11	−0.08	0.23	0.19	0.51	0.43	0.14	0.00
FF5	MKT	0.99	0.97	0.25	0.21	0.52	0.44	0.08	0.00
	SMB	0.80	0.75	0.35	0.29	0.72	0.62	0.14	0.00
	HML	0.20	0.26	0.50	0.41	1.06	0.90	0.18	0.00
	PROF	0.01	0.17	0.59	0.47	1.36	1.16	0.22	0.00
	INV	0.00	0.03	0.74	0.61	1.50	1.29	0.26	0.00
HXZ4	MKT	0.95	0.94	0.25	0.21	0.50	0.43	0.09	0.00
	SMB	0.69	0.62	0.33	0.27	0.67	0.58	0.15	0.00
	PROF	−0.22	−0.09	0.43	0.35	0.89	0.76	0.22	0.00
	INV	0.16	0.29	0.57	0.47	1.16	1.01	0.21	0.00

Panel B: Industries

CAPM	MKT	1.03	1.06	0.04	0.04	0.12	0.11	0.23	0.21
FF3	MKT	1.05	1.07	0.04	0.04	0.13	0.12	0.15	0.14
	SMB	0.17	0.17	0.06	0.06	0.20	0.18	0.17	0.17
	HML	0.23	0.25	0.07	0.06	0.21	0.19	0.32	0.32
FF4	MKT	1.03	1.06	0.04	0.04	0.14	0.12	0.13	0.13
	SMB	0.17	0.17	0.06	0.06	0.20	0.18	0.16	0.15
	HML	0.21	0.22	0.07	0.06	0.22	0.20	0.30	0.29
	MOM	−0.06	−0.07	0.04	0.04	0.14	0.13	0.16	0.15
FF5	MKT	1.07	1.10	0.05	0.04	0.15	0.13	0.12	0.12
	SMB	0.26	0.28	0.07	0.06	0.21	0.19	0.15	0.17
	HML	0.16	0.19	0.09	0.08	0.30	0.27	0.30	0.30
	PROF	0.29	0.34	0.09	0.09	0.39	0.35	0.26	0.24
	INV	0.09	0.11	0.14	0.13	0.43	0.39	0.32	0.28
HXZ4	MKT	1.04	1.08	0.05	0.04	0.15	0.13	0.11	0.09
	SMB	0.20	0.20	0.06	0.06	0.20	0.18	0.14	0.15
	PROF	0.10	0.13	0.08	0.07	0.26	0.23	0.27	0.24
	INV	0.24	0.31	0.11	0.10	0.34	0.31	0.37	0.35

all estimated to be around 0.14 and 0.17, respectively, and the average risk loadings on the profitability and investment factors have estimated true variances of at least 0.21. However, the median true variance across firms is 0.00, which indicates that any time variation in the estimated risk loadings might be driven by estimation error for a large number of firms.

The results in Table 3.2 show that one drawback of adding more factors to a model is that the standard errors by which the risk loadings are estimated increase substantially. This observation can be understood by examining the findings in Panel B of Table 3.1, which show that the factor realizations are, to varying degrees, correlated. This correlation leads to multicollinearity problems that increase estimation error in the risk loadings.

Panel B of Table 3.2 shows that the standard errors in the risk loadings are smaller for industries. The time series average mean (median) standard error of the CAPM risk loading is only 0.04 (0.04), which is substantially lower than the mean (median) value of 0.21 (0.18) that I find for individual firms. This does not necessarily imply that practitioners should use industry risk loadings instead of firm risk loadings, because another important factor that should be considered is whether industry expected returns forecast subsequent firm realized returns better than do firm expected returns. The finding for firms that standard errors increase with the number of factors in a model also applies to industries. For all factors, the implied variances of the true risk loadings are greater for industries than for firms. For instance, the risk loadings on the CAPM market factor have an average implied variance of 0.23 across industries, compared to an average of 0.12 across firms. This result is not surprising. Since the risk loading estimates are considerably more precise for industries, any variation in the estimated industry risk loadings is less likely to be driven by estimation error than any variation in the estimated firm risk loadings. Applying the two standard deviation rule, and using a market risk loading of 1.03 for the average industry, this means that the market risk loading can be between 0.57 and 1.49 at any point in time.

In summary, the results in Table 3.2 show that the risk loadings of firms are estimated with large standard errors, which suggests that their information content might be limited. To a lesser degree, this also holds for the risk loadings of industries. Moreover, the results indicate that any time variation in the estimated firm risk loadings might often be the result of estimation error. Since industry risk loadings are estimated much more precisely, any time variation in the estimates is more likely to reflect true variation.

3.5 Estimating Expected Returns

For many applications, practitioners need to combine risk premia and risk loadings to obtain expected return estimates. In this section, I describe how I estimate expected returns, and evaluate by how much the expected return estimates produced by the five models differ from each other.

3.5.1 Expected Return Point Estimates

I follow the common finance textbook method and calculate a security's expected return by multiplying the estimated risk premia by the estimated risk loadings and, if the model contains multiple factors, by taking the sum of the resulting products. In the main analysis, I use three specifications to determine the expected return estimates. In the first specification, I use the full sample arithmetic average factor realizations as risk premium estimates, along with full sample risk loadings. This process generates the *full sample expected returns.* In the second specification, I also use the full sample arithmetic average factor realizations as risk premium estimates but the risk loadings are estimated using a five-year rolling window. This process yields the *ex post rolling window expected returns.* In the third specification, I use expanding window arithmetic average factor realizations as risk premium estimates and risk loadings estimated on a five-year rolling window. This process generates the *ex ante rolling window expected returns.* The first and second specifications are also used in Fama and French (1997), and are based on information that a practitioner would not know at the time of making an investment decision. In contrast, the third specification is based on information that a practitioner would know in real time.

In Table 3.3, I report summary statistics for the realized and expected returns for

Table 3.3. Realized and Expected Excess Returns for Firms

This table shows statistics for annualized realized and expected excess returns produced by the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4) for firms. Summary statistics are displayed for expected returns based on three specifications. First, full sample expected returns are based on risk premia estimated as the full sample arithmetic average factor realizations and full sample risk loadings. Second, ex post rolling window expected returns are based on risk premia estimated as the full sample arithmetic average factor realizations and risk loadings estimated on a five year rolling window. Third, ex ante rolling window expected returns are based on risk premia estimated as the prevailing arithmetic average factor realizations and risk loadings estimated on a five year rolling window. Panel A presents the time series average of the mean and median, as well as the mean and median time series standard deviation of realized and expected excess returns. Panel B presents summary statistics for disagreement between models about expected return. The first row presents the cross-sectional average of the average time series spread between the highest and the lowest estimated expected excess returns. The second row presents the time series average of the mean standard deviation across the five expected return estimates. The next five rows correspond to the standard deviation across four models, each time excluding one of the five models considered. Panel C displays the Pearson correlation coefficients between the realized and expected returns estimated across the five models averaged across firms. I require at least 60 expected return observations to be available. The left-hand side corresponds to ex post rolling window expected returns, and the right-hand side corresponds to ex ante rolling window expected returns. The sample period is from January 1977 to December 2013.

Panel A: Realized and expected excess returns

	Full sample expected returns		Ex post rolling window expected returns				Ex ante rolling window expected returns			
	Mean	Med	Mean	Med	Mean std	Med std	Mean	Med	Mean std	Med std
Realized	9.71	12.11	9.71	12.11	50.34	47.10	9.71	12.11	50.34	47.10
CAPM	6.94	6.62	7.06	6.67	0.76	0.66	4.64	3.84	0.75	0.67
FF3	9.54	9.15	9.44	8.99	1.54	1.34	8.06	7.70	1.88	1.66
C4	8.27	8.19	8.33	8.00	2.07	1.77	6.77	6.58	2.58	2.24
FF5	8.68	9.11	8.10	8.26	2.94	2.53	6.98	7.16	2.84	2.47
HXZ4	6.66	7.49	6.37	6.78	3.02	2.62	4.71	5.25	3.53	3.08

Panel B: Disagreement about expected excess returns

	Full sample expected returns		Ex post rolling window expected returns				Ex ante rolling window expected returns			
	Mean	Med	Mean	Med	Mean std	Med std	Mean	Med	Mean std	Med std
Spread	12.99	10.38	20.29	17.58	8.40	6.80	22.30	19.29	9.25	7.49
$\sigma(E(r))$	1.51	1.21	2.36	2.05	0.97	0.78	2.60	2.25	1.06	0.85
$\sigma(E(r))^{-CAPM}$	1.41	1.09	2.34	2.00	1.07	0.87	2.48	2.10	1.16	0.93
$\sigma(E(r))^{-FF3}$	1.61	1.29	2.52	2.17	1.07	0.87	2.77	2.38	1.17	0.95
$\sigma(E(r))^{-C4}$	1.60	1.27	2.49	2.15	1.08	0.87	2.69	2.31	1.17	0.94
$\sigma(E(r))^{-FF5}$	1.44	1.11	2.14	1.81	0.96	0.77	2.58	2.20	1.14	0.93
$\sigma(E(r))^{-HXZ4}$	1.33	1.09	2.06	1.78	0.92	0.74	2.18	1.89	0.93	0.76

Panel C: Pearson correlations between expected returns averaged across firms

	Ex post rolling window expected returns					Ex ante rolling window expected returns				
	CAPM	FF3	C4	FF5	HXZ4	CAPM	FF3	C4	FF5	HXZ4
Realized	−0.01	0.01	−0.01	0.00	0.00	−0.04	0.00	−0.01	0.00	−0.01
CAPM		0.33	0.21	0.12	0.13		0.30	0.19	0.17	0.10
FF3			0.58	0.46	0.23			0.60	0.62	0.26
C4				0.37	0.48				0.47	0.50
FF5					0.43					0.44

Table 3.4. Realized and Expected Excess Returns for Industries

This table shows statistics for annualized realized and expected excess returns produced by the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4) for industries. Summary statistics are displayed for expected returns based on three specifications. First, full sample expected returns are based on risk premia estimated as the full sample arithmetic average factor realizations and full sample risk loadings. Second, ex post rolling window expected returns are based on risk premia estimated as the full sample arithmetic average factor realizations and risk loadings estimated on a five year rolling window. Third, ex ante rolling window expected returns are based on risk premia estimated as the prevailing arithmetic average factor realizations and risk loadings estimated on a five year rolling window. Panel A presents the time series average of the mean and median, as well as the mean and median time series standard deviation of realized and expected excess returns. Panel B presents summary statistics for disagreement between models about expected return. The first row presents the cross-sectional average of the average time series spread between the highest and the lowest estimated expected excess returns. The second row presents the time series average of the mean standard deviation across the five expected return estimates. The next five rows correspond to the standard deviation across four models, each time excluding one of the five models considered. Panel C displays the Pearson correlation coefficients between the realized and expected returns estimated across the five models averaged across industries. I require at least 60 expected return observations to be available. The left-hand side corresponds to ex post rolling window expected returns, and the right-hand side corresponds to ex ante rolling window expected returns. The sample period is from January 1977 to December 2013.

Panel A: Realized and expected excess returns

	Full sample expected returns		Ex post rolling window expected returns				Ex ante rolling window expected returns			
	Mean	Med	Mean	Med	Mean std	Med std	Mean	Med	Mean std	Med std
Realized	8.64	8.62	8.64	8.62	22.37	22.21	8.64	8.62	22.37	22.21
CAPM	6.50	6.68	6.45	6.60	0.48	0.43	4.39	4.43	0.77	0.75
FF3	8.10	8.47	7.57	7.44	0.70	0.69	5.82	5.67	1.12	1.12
C4	7.47	7.73	6.87	7.14	0.81	0.74	4.93	5.24	1.23	1.23
FF5	9.56	9.93	7.64	8.02	1.20	1.10	5.91	6.21	1.40	1.37
HXZ4	9.13	9.76	7.02	6.93	1.19	1.11	5.27	5.22	1.59	1.46

Panel B: Disagreement about expected excess returns

	Full sample expected returns		Ex post rolling window expected returns				Ex ante rolling window expected returns			
	Mean	Med	Mean	Med	Mean std	Med std	Mean	Med	Mean std	Med std
Spread	4.90	4.98	7.01	6.42	3.29	3.02	7.66	7.11	3.56	3.22
$\sigma(E(r))$	0.58	0.56	0.81	0.73	0.37	0.34	0.89	0.82	0.40	0.36
$\sigma(E(r))^{-CAPM}$	0.49	0.48	0.75	0.69	0.39	0.34	0.80	0.76	0.43	0.36
$\sigma(E(r))^{-FF3}$	0.64	0.61	0.87	0.80	0.42	0.41	0.95	0.87	0.45	0.41
$\sigma(E(r))^{-C4}$	0.63	0.63	0.86	0.79	0.41	0.38	0.93	0.86	0.45	0.42
$\sigma(E(r))^{-FF5}$	0.56	0.55	0.74	0.67	0.39	0.35	0.88	0.82	0.44	0.41
$\sigma(E(r))^{-HXZ4}$	0.56	0.52	0.75	0.70	0.38	0.36	0.79	0.73	0.39	0.36

Panel C: Pearson correlations between expected returns averaged across industries

	Ex post rolling window expected returns					Ex ante rolling window expected returns				
	CAPM	FF3	C4	FF5	HXZ4	CAPM	FF3	C4	FF5	HXZ4
Realized	0.01	0.03	0.02	0.01	0.02	−0.02	0.00	−0.01	−0.01	0.00
CAPM		0.05	0.03	−0.08	−0.14		0.53	0.44	0.41	0.29
FF3			0.59	0.61	0.34			0.73	0.82	0.55
C4				0.40	0.59				0.65	0.70
FF5					0.49					0.63

firms in Panel A, statistics on the dispersion in expected return estimates for firms across models in Panel B, and correlation coefficients between the expected return estimates for firms in Panel C. In Table 3.4, I present the results for industries.

The results in Panel A of Table 3.3 show that the mean annualized expected returns produced by several models are very different from each other. The time series average of the mean (median) full sample expected return produced by the Fama and French (1993) model is 9.54% (9.15%), which is close to the time series average of the mean (median) monthly realized excess return of 9.71% (12.11%). In contrast, the time series average of the mean (median) full sample expected return produced by the Hou, Xue, and Zhang (2015) model is only 6.66% (7.49%). The average expected returns produced by the other models are in-between the averages of these models. The results are similar for the ex post and ex ante rolling window expected returns. The findings show that the choice of model is important because it can lead to very different project valuations and investment decisions.

The average realized and expected excess returns have very different time series volatilities. Panel A of Table 3.3 also presents the average and median time series standard deviations of both the realized excess returns and the rolling window expected returns. Since the risk loadings are based on overlapping windows, they are persistent. It is therefore no surprise that the realized returns are much more volatile than the expected returns. For instance, the annualized average (median) time series standard deviation of realized returns is 50.34% (47.10%), while the numbers corresponding to expected returns are all lower than 4%. In addition, the expected returns produced by the CAPM have substantially less time series variation than the other models. For instance, the average (median) time series standard deviation of ex post rolling window expected returns of the CAPM is only 0.76% (0.66%), while it is 3.02% (2.62%) for the Hou, Xue, and Zhang (2015) four-factor model.

Panel A of Table 3.4 shows that the differences between realized and expected returns for industries are similar to those for firms. However, both realized and expected returns of industries are substantially less volatile than for firms, which reflect the effects of aggregation into portfolios.

3.5.2 Model Disagreement

I next analyze to what extent the models generate conflicting results for expected excess returns. I calculate for each firm and in every month (1) the range between the highest and lowest monthly expected excess return, and (2) the standard deviation over the five expected return estimates. The range is driven by extreme values and is easy interpretable. In contrast, the standard deviation is less subject to extreme values, but harder to interpret because it is based on only five observations.

The results in Panel B of Table 3.3 show that, on average, the monthly range of expected return estimates is large. The annualized time series average of the mean (median) spread between the full sample estimates is 12.99% (10.38%). The results are more extreme for rolling window expected returns. Specifically, the annualized time series average of the mean (median) range across firms is 20.29% (17.58%) for ex post rolling window expected returns. The time series standard deviation of this measure shows that the degree of conflict between the expected return estimates varies substantially over time. The results confirm that there are substantial differences between the expected returns of the different models, along with considerable variation across time.

To examine whether there is one model that produces estimates of expected returns that are consistently different from the ones produced by the other models, I first calculate the mean (median) monthly standard deviation between the expected returns averaged across firms, and then I re-estimate the standard deviation, each time excluding one of the five observations. The idea is that taking out a model that produces expected return estimates that are different from the ones produced by the other models results in a decrease in the cross-sectional standard deviation, and vice versa. I present the results in the bottom rows of Panel B of Table 3.3. If the estimates by the Fama and French (1993) or the Carhart (1997) model are excluded from the set of expected returns, the standard deviation increases marginally, while for the other models it decreases marginally. The changes are small, suggesting that none of the five models consistently produces different expected return estimates. Thus, the conflicting expected return estimates are not driven by one particular model.

The results in Panel B of Table 3.4 demonstrate that portfolio aggregation leads to a large decrease in disagreement about expected return estimates. The time series average of the annualized mean (median) spread between the highest and lowest full sample expected return estimate for industries is 4.90% (4.98%), while the time series average of the annualized mean (median) spread between the highest and lowest rolling window expected return estimates is 7.01% (6.42%). Although uncertainty about expected returns due to model misspecification is substantially less for industries than for firms, it is still large. Industries exhibit less time variation than firms in model disagreement, indicating that expected return estimates are more stable relative to those of firms. Therefore, the conclusion that the choice of asset pricing model generally results in very different expected return estimates also holds for industries.

The finding that asset pricing models generate expected returns that differ greatly for both firms and industries raises the question of whether they are actually correlated over time. To address this, I calculate the average time series correlation of the expected returns produced by the five models and examine in which periods the estimates of the models are dissimilar.

Panel C of Tables 3.3 and 3.4 presents the Pearson correlations of the expected returns estimates averaged across firms and industries, respectively. The results show that the expected returns of firms are positively correlated, although the correlation is less than perfect. For ex post rolling window expected returns, the average correlation ranges from 0.12 between the CAPM and the Fama and French (2015) five-factor model, to 0.58 between the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. Surprisingly, the expected returns produced by the Fama and French (2015) five-factor model and the Hou, Xue, and Zhang (2015) four-factor model, both including a profitability and an investment factor, have a relatively low correlation of 0.43, while the correlations between the factors are high. Panel C of Table 3.4 shows that the correlations show a similar pattern for industries, although they are negative in some cases. For instance, the average correlation coefficient is −0.08 between the CAPM and the Fama and French (2015) model, and is −0.14 between the CAPM and the Hou, Xue, and Zhang (2015) model. The results are similar for ex ante rolling window expected returns.

The results in Tables 3.3 and 3.4 show that the expected return estimates produced by the five models are dissimilar. The correlations between the estimates are low, which means that there is little agreement on time variation. Due to the varying estimated expected returns from the five asset pricing models examined here, CFOs and investors should be very careful in selecting which model to employ to make their investment decisions.

3.6 Estimation Error in Expected Returns

In addition to the issue of selecting the most appropriate asset pricing model, estimation errors in risk premia and risk loadings are issues that practitioners need to address. Estimation errors are important as they increase the imprecision by which expected returns are calculated and, consequently, how investment projects are valued. In this section, I discuss the calculation of the standard errors of the expected return estimates and compare them between models. Next, I use the standard errors to examine whether the expected return estimates provided by the five models differ statistically from each other.

3.6.1 Standard Errors

I follow Fama and French (1997) and determine the standard error by which an expected return is estimated as follows:

$$SE(ER) = \sqrt{F'\mathrm{var}(\varepsilon_\beta)F + \beta'\mathrm{var}(\varepsilon_F)\beta + I'(\mathrm{var}(\varepsilon_F) \circ \mathrm{var}(\varepsilon_\beta))I}, \tag{3.6}$$

where F is a vector of estimated annualized factor premia (see Table 3.1), $\mathrm{var}(\varepsilon_F)$ is the estimated covariance matrix of the annualized factor premia, β is the estimated vector of risk loadings (see Table 3.2), $\mathrm{var}(\varepsilon_\beta)$ is the covariance matrix of the standard errors of the risk loadings, I is a vector of ones, and $\circ$ is the Hadamard product. I assume that the returns are multivariate normally distributed, which implies that $cov(\varepsilon_i, \varepsilon_j) = 0$ for $i \neq j$.

Table 3.5. Standard Errors Expected Returns

This table shows annualized mean and median standard errors of the expected return estimates produced by the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). I calculate the standard error of the expected return following Fama and French (1997). In particular, I estimate

$$SE(ER) = \sqrt{\boldsymbol{F}'\mathrm{var}(\boldsymbol{\varepsilon_\beta})\boldsymbol{F} + \boldsymbol{\beta}'\mathrm{var}(\boldsymbol{\varepsilon_F})\boldsymbol{\beta} + \boldsymbol{I}'(\mathrm{var}(\boldsymbol{\varepsilon_F}) \circ \mathrm{var}(\boldsymbol{\varepsilon_\beta}))\boldsymbol{I}}$$

where $\boldsymbol{F}$ is the vector of annualized factor premia, $\mathrm{var}(\boldsymbol{\varepsilon_F})$ the covariance matrix of the annualized factor premia, $\boldsymbol{\beta}$ the vector of risk loadings, and $\mathrm{var}(\boldsymbol{\varepsilon_\beta})$ the covariance matrix of the standard errors of the risk loadings. The term $\mathrm{var}(\boldsymbol{\varepsilon_F})$ is set to zero in rows 1 and 2, thereby assuming that risk premia are estimated without error. In row 3 the term $\mathrm{var}(\boldsymbol{\varepsilon_\beta})$ is set to zero, thereby assuming that risk loadings are estimated without error. In rows 1 and 4, I use the risk loadings from full sample regressions. In rows 2 and 5, I use the time series average covariance matrix from five year monthly rolling window regressions. Panel A reports the average and median (in parentheses) standard error across firms. The results for industries are reported in panel B. The sample period is from January 1977 to December 2013.

Panel A: Firms

	CAPM	FF3	C4	FF5	HXZ4
Risk premia estimated without error					
(1) Full-period regressions	1.79	3.81	5.18	6.90	7.58
	(1.55)	(3.07)	(4.31)	(5.95)	(6.44)
(2) Rolling 5-year regressions	3.05	6.80	9.41	13.42	13.69
	(2.65)	(5.78)	(8.13)	(11.85)	(12.16)
Risk premia estimated with error					
(3) No error in risk loadings	2.72	3.52	3.70	3.86	3.61
	(2.58)	(3.31)	(3.46)	(3.59)	(3.37)
(4) Full-period regressions	3.47	5.54	6.71	8.29	8.69
	(3.22)	(4.94)	(5.92)	(7.32)	(7.57)
(5) Rolling 5-year regressions	4.42	8.14	10.62	14.47	14.51
	(4.05)	(7.21)	(9.42)	(12.92)	(12.96)

Panel B: Industries

	CAPM	FF3	C4	FF5	HXZ4
Risk premia estimated without error					
(1) Full-period regressions	0.27	0.50	0.69	0.78	0.97
	(0.26)	(0.47)	(0.67)	(0.74)	(0.91)
(2) Rolling 5-year regressions	0.79	1.65	2.22	3.12	3.35
	(0.75)	(1.53)	(2.06)	(2.91)	(3.14)
Risk premia estimated with error					
(3) No error in risk loadings	2.54	2.64	2.66	2.71	2.65
	(2.61)	(2.76)	(2.77)	(2.81)	(2.76)
(4) Full-period regressions	2.56	2.71	2.77	2.85	2.86
	(2.62)	(2.81)	(2.86)	(2.92)	(2.95)
(5) Rolling 5-year regressions	2.70	3.23	3.59	4.28	4.39
	(2.73)	(3.25)	(3.56)	(4.07)	(4.22)

Table 3.5 presents summary statistics for the standard errors of the expected return estimates. The table reports time series averages of the mean and median standard error of full sample and ex post rolling window expected return estimates. To better understand the source of the estimation errors, I examine the contribution of estimation errors in the risk premia and those in the risk loadings to the estimation errors in the expected return estimates. To this end, I follow Fama and French (1997) and calculate the standard errors under the assumption that the risk premia or the risk loadings are estimated without errors.

Panel A of Table 3.5 presents summary statistics for the standard errors of expected returns for firms and Panel B presents corresponding summary statistics for industries. The results in Panel A show that, if the risk premia contain no estimation error, the standard errors are substantial. I find that the annualized mean (median) standard error is 1.79% (1.55%) for the CAPM, while it is 7.58% (6.44%) for the Hou, Xue, and Zhang (2015) model. The values for the Fama and French (1993), Carhart (1997), and Fama and French (2015) models are intermediate. If I allow the risk loadings to vary over time, the mean standard error increases to 3.05% (2.65%) per year for the CAPM and 13.69% (12.16%) per year for the Hou, Xue, and Zhang (2015) model. Therefore, even if the risk premia could be determined with certainty, estimation error in the risk loadings still leads to expected returns that are estimated with tremendous imprecision.

I next examine the problems that uncertainty in the risk premia cause in the estimation of expected returns by setting the estimation errors in the risk loadings equal to zero and allowing for estimation errors in risk premia. The results in Table 3.5 show that the mean standard errors are also substantial under these assumptions, although they are lower than when I only allow for estimation error in the risk loadings. I find a mean (median) standard error of 2.72% (2.58%) per year for the CAPM and 3.86% (3.59%) per year for the Fama and French (2015) model. The results for the other models are intermediate. As with the risk loadings, estimation error in the risk premia contributes greatly to the imprecision in estimated expected returns.

Given that both risk loadings and premia are extremely imprecise, the estimation errors of the expected return estimates are also extreme. Table 3.5 shows that, for the full sample expected returns, the mean (median) standard error ranges from 3.47% (3.22%) per year for the CAPM to 8.69% (7.57%) per year for the Hou, Xue, and Zhang (2015) model. For ex post rolling window expected returns, the mean standard errors are even greater. For the CAPM, the mean (median) standard error is 4.42% (4.05%) per year while for the Hou, Xue, and Zhang (2015) model it is 14.51% (12.96%) per year. Thus, the results show that estimated expected returns have large standard errors, and raise questions about the usefulness of these models in determining accurate costs of equity for firms.

Panel B of Table 3.5 shows that the standard errors of the expected return estimates are much lower for industries. For full sample expected returns, the mean (median) standard error for the CAPM is 2.56% (2.62%) per year, almost 1% lower compared to firms. For the Hou, Xue, and Zhang (2015) model, the corresponding number is 2.86% (2.95%) per year, which is more than 5% lower than that for firms. For ex post rolling window expected returns, the mean (median) standard error is 2.70% (2.73%) per year, while for the Hou, Xue, and Zhang (2015) model it is 4.39% (4.22%) per year. The difference between the average industry and firm expected return standard errors is almost 10%. Thus, the findings show that the industry expected returns are relatively precise.

The results indicate that, for multi-factor models, the bulk of the estimation error in the expected return estimates of firms is driven by estimation error in the risk loadings. In contrast, estimation error in the risk loadings and premia contribute approximately equally to the estimation error in the expected return estimates produced by the CAPM. For full sample expected returns, the mean (median) CAPM standard error increases from 1.79% (1.55%) per year if the risk premium is estimated without error to 3.47% (3.22%) per year if the risk premium is estimated with error. The mean (median) error is a hefty 7.58% (6.44%) per year for the Hou, Xue, and Zhang (2015) model when risk premia are estimated without error, and it increases to 8.69% (7.57%) per year when the standard errors of the risk premia are incorporated. Thus, my evidence confirms the results by Fama and French (1997) that the largest part of the estimation error in expected returns comes from estimation error in the risk premia for the CAPM, and to a lesser extent for the Fama and French (1993) model. However, the biggest part of the estimation error in expected returns comes from estimation error in the risk loadings in the Carhart (1997), Fama and French (2015), and Hou, Xue, and Zhang (2015) models. The results are similar for rolling window expected returns.

For industries, the mean CAPM standard error of the expected return estimates is 0.27% per year when the estimation error in the risk premium is ignored, while the mean error is 2.56% per year when it is incorporated. For the Hou, Xue, and Zhang (2015) model, the corresponding estimation errors are 0.97% and 2.86%, respectively. These numbers show that a large part of the industry expected return standard errors are still driven by estimation errors in risk premia, which is because risk loadings are estimated more precisely for industries than for firms.

To better understand why the standard errors of expected returns by multi-factor models are mainly driven by the errors in the risk loadings, I compare the firm average standard error of the market risk loading for the CAPM and the Fama and French (2015) model over time. As can be seen in Figure 3.2, the average standard error for the loading on the market factor in the Fama and French (2015) model is less precisely estimated than the average loading on the CAPM market factor. In particular, the standard error is on average around 30% higher relative to the CAPM. The figure also shows that the estimates contain more noise during volatile periods, such as the collapse of the Internet Bubble and the Global Financial Crisis.

To analyze when practitioners should be especially concerned about estimation error in expected returns, I plot the median standard errors of the expected return estimates for firms over time and present the results in Figure 3.3. The figure shows that the median standard errors are positively correlated across time. In general, the CAPM has the smallest standard error, followed by the Fama and French (1993) and Carhart (1997) models. In some periods, the average standard error of the Fama and French (2015) five-factor model is highest, while in other periods the standard error of the Hou, Xue, and Zhang (2015) four-factor model is highest. Finally, the error terms

Figure 3.2. Time Series Standard Error of Risk Factor Loadings on Market Factor

This figure shows the average time series standard error of risk loadings on the market factor across firms for the CAPM and the Fama and French (2015) five-factor model (FF5). The risk loadings are estimated on a five-year rolling window. The sample period is from January 1977 to December 2013.

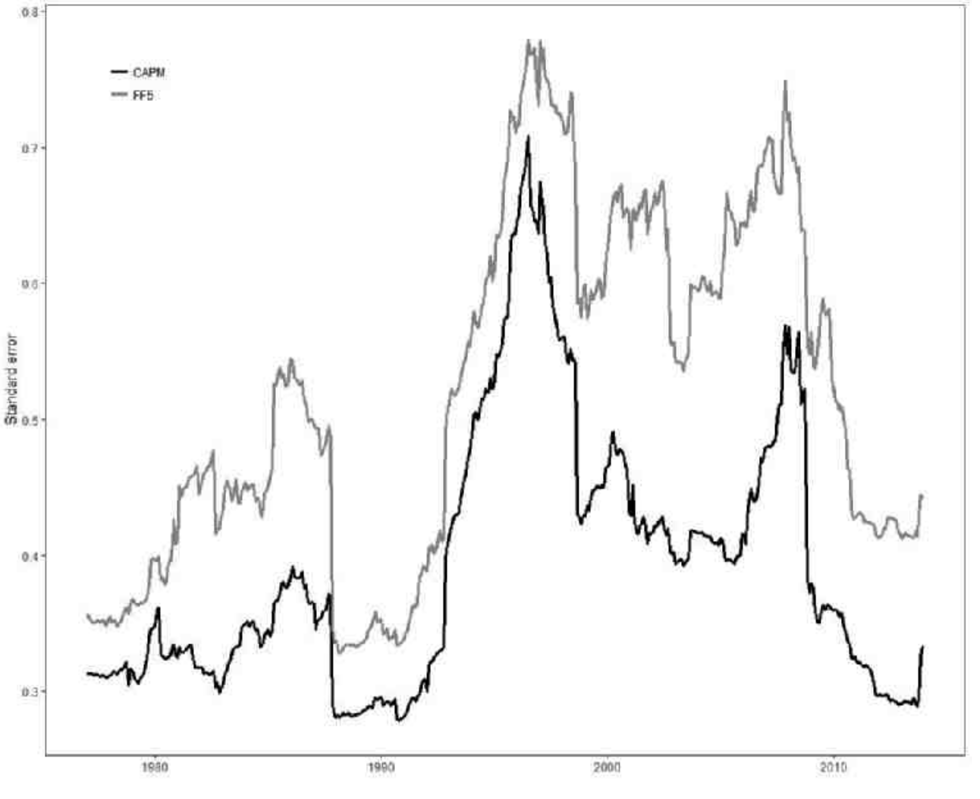


Figure 3.3. Time Series of Standard Errors Expected Returns for Firms

This figure shows the median standard error of expected returns from five different models for firms from January 1977 to December 2013. The five models are the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). I calculate the standard error of the expected return following Fama and French (1997). In particular, I estimate

$$SE(ER) = \sqrt{F'\text{var}(\varepsilon_\beta)F + \beta'\text{var}(\varepsilon_F)\beta + I'(\text{var}(\varepsilon_F) \circ \text{var}(\varepsilon_\beta))I}$$

where F is the vector of annualized factor premia, $\text{var}(\varepsilon_F)$ the covariance matrix of the annualized factor premia, β the vector of risk loadings, and $\text{var}(\varepsilon_\beta)$ the covariance matrix of the standard errors of the risk loadings on five year rolling window regressions.

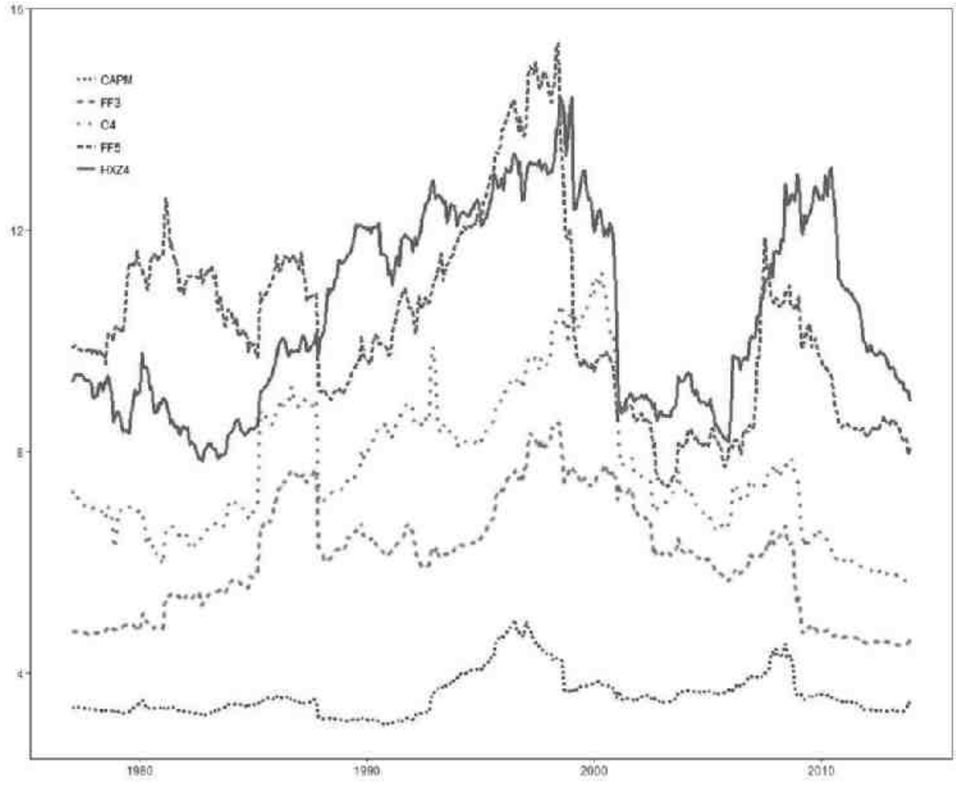


Table 3.6. Time Series Correlations Standard Errors of Expected Returns

This table shows average time series correlations between the standard errors of expected returns produced by the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). I calculate the standard error of the expected return following Fama and French (1997). In particular, I estimate

$$SE(ER) = \sqrt{F'\mathrm{var}(\varepsilon_\beta)F + \beta'\mathrm{var}(\varepsilon_F)\beta + I'(\mathrm{var}(\varepsilon_F) \circ \mathrm{var}(\varepsilon_\beta))I}$$

where F is the vector of annualized factor premia, $\mathrm{var}(\varepsilon_F)$ the covariance matrix of the annualized factor premia, β the vector of risk loadings, and $\mathrm{var}(\varepsilon_\beta)$ the covariance matrix of the standard errors of the risk loadings. Panel A shows the results for firms and Panel B shows the results for industries. The sample period is from January 1977 to December 2013.

Panel A: Firms

	FF3	C4	FF5	HXZ4
CAPM	0.76	0.75	0.81	0.75
FF3		0.88	0.79	0.74
C4			0.77	0.83
FF5				0.80

Panel B: Industries

	FF3	C4	FF5	HXZ4
CAPM	0.66	0.59	0.49	0.59
FF3		0.87	0.46	0.49
C4			0.52	0.64
FF5				0.53

are relatively large towards the end of the twentieth century and after the Global Financial Crisis. For example, the median standard error of the Hou, Xue, and Zhang (2015) model increases to levels above 16% at the end of the twentieth century, and grows from less than 10% in 2007 to around 12% in 2008-2009. Untabulated results show that the time series pattern for industries is similar to that for firms.

The standard errors for the models are correlated over time, as shown in Figure 3.3. However, positive correlations are not surprising, since the standard errors are based on risk factors that are similar or common across the five models. I test this more formally by calculating the time series correlation of standard errors across models for all firms and industries. The results in Table 3.6 confirm that the standard errors of the expected return estimates across the models are highly correlated. For firms, the correlations range from 0.74 to 0.88. For industries, the correlations are lower and range from 0.46 to 0.87.

In addition to realizing that the expected returns across models are very different, CFOs and investors should also realize that those returns are estimated with large

Table 3.7. Statistical Disagreement

This table reports the results for two-sample t-tests of differences between expected returns produced by the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). The numbers indicate the time series average of the fraction of firms for which the null hypothesis of no significance between the ex post rolling window expected returns cannot be rejected. The left- and right-hand side present the results for a 5% and 10% critical value, respectively. The sample period is from January 1977 to December 2013. The results for firms are presented in Panel A and Panel B shows the results for industries.

Panel A: Firms

5%	FF3	C4	FF5	HXZ4	10%	FF3	C4	FF5	HXZ4
CAPM	0.963	0.959	0.933	0.936	CAPM	0.923	0.918	0.875	0.883
FF3		0.999	0.986	0.963	FF3		0.987	0.964	0.923
C4			0.984	0.993	C4			0.961	0.978
FF5				0.989	FF5				0.969

Panel B: Industries

5%	FF3	C4	FF5	HXZ4	10%	FF3	C4	FF5	HXZ4
CAPM	0.973	0.976	0.922	0.935	CAPM	0.934	0.949	0.864	0.883
FF3		0.999	0.990	0.973	FF3		0.993	0.971	0.938
C4			0.970	0.995	C4			0.941	0.981
FF5				0.985	FF5				0.966

errors. The standard errors are a problem, and should be taken into consideration when judging the usefulness of an asset pricing model. Using industries as test assets instead of firms helps to decrease standard errors, although they remain large.

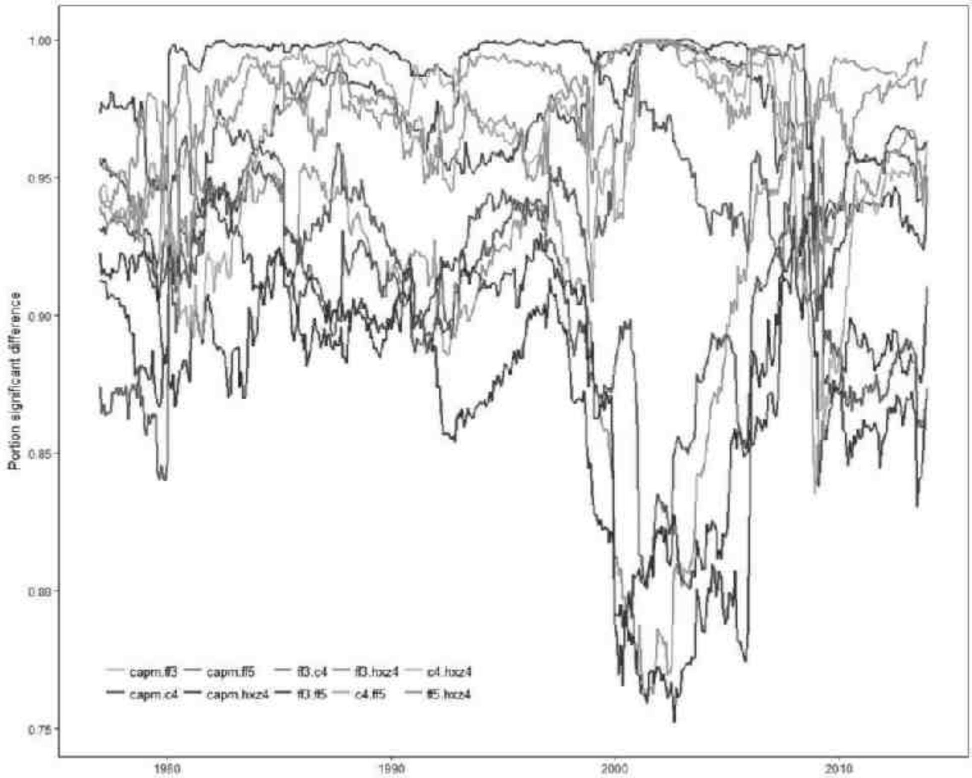
3.6.2 Disagreement from a Statistical Viewpoint

I have shown that differences between the point estimates of expected returns are large from an economic viewpoint. However, as shown in Table 3.6, the expected returns are estimated imprecisely. To test whether they are different statistically, I run cross-sectional two-sample t-tests for every month in the sample period to compare the expected return estimates between two models. In Table 3.7, I report the time series average fraction of firms and industries for which the two-sample t-test cannot reject the hypothesis that the expected return estimates between two models are equal. Panels A and B show the results for firms and industries, respectively.

Panel A of Table 3.7 shows that, in almost all cases, the expected returns are not different from each other at the usual significance levels. From all combinations of two models from the set of five, the expected returns produced by the CAPM and the Fama and French (2015) model differ most often on average. However, the

Figure 3.4. Time Series Differences Expected Returns

This figure shows the evolution of the results of two-sample t-test of differences between expected returns for the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). The lines indicate the fraction of firms for which the null hypothesis of no significant difference between expected returns cannot be rejected at the ten percent level. The sample period is from January 1977 to December 2013.



expected return estimates cannot be discriminated statistically at the 5% (10%) level of significance for 93.3% (87.5%) of the firms. Panel B of Table 3.7 shows that the results are similar for industries.

Figure 3.4 shows the fractions of firms for which the null hypothesis of no differences between the expected return estimates cannot be rejected over time. For 2000-2007, the CAPM produces expected returns that are statistically different from those produced by the other four models for roughly 20% of the firms. Although there is time variation in the number of firms with statistically different expected return estimates, those expected returns are not statistically different from each other for almost all firms at any point in time.

The results in Table 3.5 show that the standard errors of the expected returns produced by the five models are enormous. As a result, the estimated expected returns are generally not different from each other statistically, which can be seen from Table 3.7. The large standard errors could be a reason to be indifferent between, or even refrain from, using asset pricing models to compute the cost of equity capital or expected returns.

3.7 Out-of-Sample Forecast Performance

Should any of the five asset pricing models I evaluate actually be used by managers and investors to compute the cost of equity capital or expected returns? The use of an asset pricing model could be justified if the model-implied expected returns provide sufficient explanatory power for subsequent realized returns. In this section, I examine the out-of-sample forecasting ability of the five models using Fama and MacBeth (1973) regressions and by sorting firms and industries into portfolios based on their expected returns.

I consider various forecasting horizons ranging from one month up to five years. On the one hand, investors with short investment horizons might be interested in the predictive ability of a model in the short run. On the other hand, CFOs might be especially interested in long-term expected returns for capital budgeting purposes. If asset pricing models are useful in this regard, then high expected returns should be associated with high realized returns in the long run, and vice versa.

To test whether expected returns are predictive of realized returns, I use Fama and MacBeth (1973) cross-sectional regressions. In particular, I estimate:

$$r_{i,t,t+k} = \gamma_0 + \gamma_1 \hat{E}_t(r_{i,t,t+k}) + \epsilon_i, \forall t, \tag{3.7}$$

where $r_{t+k} = \prod_{j=t}^{t+k}(1 + r_{i,j}) - 1$ is a firm or industry's k-month realized return, and $\hat{E}_t(r_{i,t,t+k}) = \hat{\beta}'_{i,t}\hat{E}_t(F_{t,t+k})$ is the corresponding estimated k-month expected return. The compounded factor premia are based on the weighted unbiased estimator of Blume (1974). This estimator is a weighted average of the compounded prevailing arithmetic average factor return (which is upward biased) and the compounded prevailing geometric average factor return (which is downward biased). Since there is autocorrelation introduced in the slope coefficients due to overlap in long-horizon returns, regular Fama and MacBeth (1973) t-statistics will be biased. I therefore use a Newey and West (1987) correction to account for this autocorrelation.

Tables 3.8 and 3.9 report results for a set of Fama and MacBeth (1973) regressions for firms and industries, respectively. I report average slope coefficients, t-statistics, average time series R^2s, the mean absolute forecast error, and the number of firms or industries included in the sample. The sample period examined in the regressions is January 1977 to December 2013. I report the results for one-month, one-year, and five-year-ahead forecasts. I use a Newey and West (1987) correction with eleven lags for yearly returns and 59 lags for five-year returns.[8] Results are reported for expected returns which are estimated from risk premia and risk loadings estimated before the realized returns are observed. I use prevailing average factor realizations to estimate risk premia. Except for the market factor, I use a common sample period (beginning in January 1972) for the risk factors. Since the market factor is included in all five models, I use the prevailing average over the period starting in 1926.[9] For the risk loadings, I use a five-year rolling window. The results are qualitatively similar when I use the Vasicek (1973) shrinkage method and other common methods to estimate the risk loadings.[10]

Table 3.8 illustrates that expected returns are only weakly related to subsequent realized returns. The slope coefficients are positive for all models, but only the one corresponding to the Fama and French (1993) model is statistically significant (t-statistic = 1.81). The pricing errors, however, are large. On average, the one-month-ahead realized returns differ from the expected returns by almost 9.7% for all the models. This evidence suggests that these models provide limited guidance for

[8] Ang, Chen, and Xing (2006) and Cremers, Halling, and Weinbaum (2015) add one additional lag for robustness. My results are similar when adding this additional lag.

[9] Since Table 3.1 shows that the correlation coefficient between the CAPM and Hou, Xue, and Zhang (2015) market factor is 1.00, I assume that realizations of the Hou, Xue, and Zhang (2015) market factor prior to 1972 are identical to the realizations of the CAPM market factor.

[10] I report results for Vasicek (1973)-adjusted five-year rolling window risk loadings, three-year rolling window risk loadings, expanding window risk loadings, and industry risk loadings in Table 3.C.1 of Appendix 3.C.

Table 3.8. Expected Versus Realized Returns for Firms

This table presents results for Fama and MacBeth (1973) regressions of expected returns on realized returns for firms. For each regression I report the coefficient, t-statistic, and R^2. I also report the time series average of the mean absolute forecast error (MAFE) and the number of firms in the sample (N). The expected return estimates are from the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). The table shows results for one-month, one-year, and five-year-ahead forecasts. To control for overlapping observations, I use a Newey and West (1987) correction with eleven lags for yearly returns, and 59 lags for five-year returns. I also present results for a subgroup of firms. The subgroups are formed by sorting firms into three portfolios based on the standard errors of the expected return estimates, and rebalancing every month. The sample period is from January 1977 to December 2013.

	All firms				Low SE(ER)				Medium SE(ER)				High SE(ER)			
	Coef	t-stat	R^2	MAFE	Coef	t-stat	R^2	MAFE	Coef	t-stat	R^2	MAFE	Coef	t-stat	R^2	MAFE
One-month-ahead forecasts																
CAPM	0.14	0.63	0.018	9.67	0.33	1.71	0.010	6.21	0.00	0.01	0.005	9.32	−0.16	−1.02	0.006	13.47
FF3	0.23	1.81	0.007	9.67	0.50	3.37	0.010	5.98	0.25	2.13	0.005	9.41	0.15	1.58	0.004	13.61
C4	0.09	0.97	0.006	9.67	0.33	2.61	0.010	6.00	0.14	1.43	0.005	9.44	0.03	0.43	0.003	13.59
FF5	0.04	0.87	0.003	9.69	0.13	1.82	0.009	6.03	0.06	1.05	0.005	9.47	0.05	1.23	0.002	13.57
HXZ4	0.03	0.55	0.005	9.69	0.13	1.83	0.009	6.02	0.06	1.23	0.004	9.47	0.02	0.52	0.003	13.60
N = 12,815																
One-year-ahead forecasts																
CAPM	0.08	0.34	0.019	38.04	0.11	0.71	0.010	24.59	−0.17	−1.03	0.006	35.98	−0.19	−1.20	0.006	53.55
FF3	0.18	1.49	0.007	37.94	0.37	3.22	0.012	23.14	0.19	1.71	0.005	37.05	0.11	1.13	0.004	53.63
C4	0.05	0.61	0.006	38.11	0.27	2.89	0.011	23.20	0.08	0.98	0.005	37.44	−0.02	−0.43	0.002	53.69
FF5	0.04	0.79	0.004	38.49	0.12	2.41	0.008	23.63	0.06	1.11	0.006	37.95	0.04	1.00	0.003	53.89
HXZ4	0.03	0.67	0.005	38.74	0.10	1.73	0.009	23.58	0.06	1.34	0.004	38.05	0.01	0.31	0.002	54.59
N = 12,815																
Five-year-ahead forecasts																
CAPM	−0.19	−1.51	0.010	100.11	0.03	0.24	0.005	68.46	−0.17	−1.09	0.006	95.43	−0.21	−2.23	0.005	136.45
FF3	0.03	0.41	0.004	98.00	0.26	3.02	0.008	65.20	0.14	2.82	0.002	98.21	0.02	0.43	0.002	130.62
C4	−0.06	−1.22	0.003	100.24	0.14	2.25	0.005	66.27	0.00	0.04	0.002	100.48	−0.06	−2.15	0.001	133.98
FF5	0.03	1.33	0.002	104.22	0.10	2.71	0.004	70.17	0.04	1.14	0.002	104.32	0.02	0.99	0.002	138.20
HXZ4	−0.01	−0.36	0.002	107.95	0.04	1.12	0.004	70.46	0.02	1.35	0.002	106.29	0.01	0.32	0.001	147.13
N = 12,571																

Table 3.9. Expected Versus Realized Returns for Industries

This table presents results for Fama and MacBeth (1973) regressions of expected returns on realized returns for industries. For each regression I report the coefficient, t-statistic, and R^2. I also report the time series average of the mean absolute forecast error (MAFE) and the number of firms in the sample (N). The expected return estimates are from the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). The table shows results for one-month, one-year, and five-year-ahead forecasts. To control for overlapping observations, I use a Newey and West (1987) correction with eleven lags for yearly returns, and 59 lags for five-year returns. I also present results for a subgroup of industries. The subgroups are formed by sorting industries into three groups based on the standard error of the expected return estimates, and rebalancing every month. The sample period is from January 1977 to December 2013.

	Coef	t-stat	R^2	MAFE
One-month-ahead forecasts				
CAPM	0.32	0.79	0.102	4.83
FF3	0.44	1.50	0.074	4.83
C4	0.57	2.18	0.075	4.83
FF5	0.19	1.18	0.064	4.84
HXZ4	0.48	2.89	0.070	4.83
$N = 48$				
One-year-ahead forecasts				
CAPM	0.30	0.75	0.119	18.55
FF3	0.34	1.25	0.089	18.50
C4	0.34	1.61	0.082	18.48
FF5	0.19	1.27	0.069	18.75
HXZ4	0.38	2.41	0.081	18.55
$N = 48$				
Five-year-ahead forecasts				
CAPM	−0.13	−0.29	0.112	49.40
FF3	−0.04	−0.20	0.045	47.67
C4	−0.13	−0.52	0.064	48.32
FF5	0.09	0.69	0.047	48.59
HXZ4	0.07	0.45	0.061	49.96
$N = 48$				

capital budgeting and investment decision-making. Note that the forecasting ability of the asset pricing models is unrelated to the number of factors included in them.

Given that the expected returns are estimated with large errors, I examine whether estimation error is an important determinant of forecasting accuracy. The idea is that noisy estimates contain less information about "true" expected returns than precise estimates, which should be reflected in a relatively poor forecasting ability. To investigate this, I sort firms into three groups based on estimation error in the expected return estimates, and rebalance them every month. I then run separate Fama and MacBeth (1973) regressions on the lowest, middle, and highest terciles, and examine for which tercile the forecasting ability is strongest.

The results in Table 3.8 show that precise estimates have better forecasting ability than noisy estimates, and that the forecast errors are lower. For the low standard error tercile, the slope coefficients on the expected return estimates produced by the Fama and French (1993), Carhart (1997), and Fama and French (2015) models are highly statistically significant, while those on the expected returns produced by the other two models are close to being significant at the 5% level. However, the slope coefficients are far away from one, indicating that the expected return estimates are far from being perfect. Nevertheless, the expected returns that are estimated relatively precisely are positively related to future realized returns. The significance levels drop when expected returns are estimated less precisely, leaving only the slope coefficients corresponding to the Fama and French (1993) expected returns statistically significant in the medium standard error tercile. Examining the high standard error tercile, which contains firms with the most noisy estimates, reveals that none of the slope coefficients are significant. This indicates that the most noisy expected return estimates do not align with subsequent realized returns. The forecast errors also increase when expected returns contain more noise. The mean absolute forecast error increases from approximately 6% for the low standard error tercile, to over 9% and 13% for the medium and high standard error terciles, respectively. For one-month-ahead forecasts, the expected returns are informative about future realized returns only when they are estimated precisely, and the forecast errors of precise estimates are relatively low.

The results in Table 3.8 for long-horizon returns show a similar pattern. Examining the one-year-ahead forecasts, all slope coefficients are positive but none are statistically significant. For the five-year-ahead forecasts, the slope coefficients of the Fama and French (1993) and Fama and French (2015) models are positive but not statistically significant, while the ones corresponding to the other models are negative but also not significant. The mean absolute pricing errors are much larger than those for one-month-ahead returns, and range from around 38% for one-year-ahead returns to a massive 100% for five-year-ahead returns. Thus, the results suggest the models have no, or at best very limited, predictive ability for future firm returns.

Precise estimates about long-term expected returns are more informative about future long-term returns than noisy estimates. In Table 3.8, for the low standard error tercile, all models have positive coefficients, and the Fama and French (1993), Carhart (1997), and the Fama and French (2015) models have t-statistics larger than 2. This evidence shows that expected returns do forecast future returns when the expected return estimates are precise. The Fama and French (1993), Carhart (1997), and the Fama and French (2015) models also forecast returns one- and five-years ahead. The forecast power generally decreases for the terciles with medium and high standard errors. The CAPM slope coefficients are even negative and statistically significant when forecasting one-year and five-year returns. This means that realized returns are opposite the forecasts of the models in the long run when those forecasts are imprecise. Note that the forecast errors are large. For one-year-ahead returns, the mean absolute pricing errors are approximately 23% – 24% for the low standard error tercile, 36% – 38% for the medium standard error tercile, and 53% – 54% for the high standard error tercile. For five-year-ahead returns, the pricing errors are even larger. The mean absolute pricing errors are approximately 65% – 70% for the low standard error tercile, 95% – 1046% for the medium standard error tercile, and 130% – 147% for the high standard error tercile. Thus, although expected returns that are precisely estimated are informative about future realized returns, they still have strikingly high forecast errors.

The results have important implications for practitioners, namely that estimation error is an important factor in determining whether or not to use asset pricing models for estimating costs of equity capital. If the estimates are relatively precise, then they are informative about true expected returns. Asset pricing models fail dismally if the estimates are imprecise.

Table 3.9 presents the results for industries. Looking at the one-month-ahead forecasts, all models have positive coefficients, some of which are statistically significant. The Hou, Xue, and Zhang (2015) model has the largest *t*-statistics, followed by the Carhart (1997) and Fama and French (2015) models. Thus, there is evidence that the models forecast out-of-sample industry expected returns. For the one-year-ahead forecasts, the slope coefficients are again all positive and are, or are close to being, statistically significant. Examining the five-year-ahead forecasts, three out of five slope coefficients are negative, although none are statistically significant. The results for the standard error terciles do not show a clear relation between estimation accuracy and forecasting ability. In contrast to firms, the expected returns for all industries are estimated relatively precisely with little cross-sectional dispersion in their standard errors. Moreover, since I have only 48 industry portfolios, I do not sort industries into portfolios based on the expected return standard errors.

Since the expected return estimates of industries are much more precise than those of firms, a CFO might be tempted to use the industry cost of equity capital. To investigate whether this would result in better forecasting performance, I run Fama and MacBeth (1973) cross-sectional regressions using industry expected returns to forecast firm returns. I match industry expected returns to the firm data using the sic codes from Kenneth French's Data Library. The results, however, show that the forecasting performance does not improve and that the forecast errors are of similar magnitude at any of the forecast horizons.[11] The results are consistent with Levi and Welch (2014) and Levi and Welch (2017).

Overall, both firm and industry returns seem to have some forecast ability at the monthly horizon. In general, the forecasting ability decreases with increasing

[11]The regression coefficients are reported in Table 3.C.1 of Appendix 3.C.

Table 3.10. Expected Return Portfolios

This table presents results of out-of-sample one-month-ahead forecasts of expected return estimates produced by the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). I estimate risk loadings on a 60 month window and risk premia based on an expanding window. Both estimates are based on data prior to the return realization. Firms are sorted each month into ten portfolios based on their expected return estimates, and industries are sorted into five portfolios. The table reports the value-weighted monthly expected and realized portfolio excess returns. For firms, I report the spread between the top and bottom portfolios (10 – 1 spread), the spread between the second and ninth decile portfolio (9 – 2 spread), and the corresponding *t*-statistics. For industries, I report the spread between the top and bottom quantile portfolios (5 – 1 spread) and corresponding *t*-statistics. The portfolios are rebalanced monthly. Panel A presents results for firms, and Panel B presents results for industries. The sample period is from January 1977 to December 2013.

Panel A: Firms

	Expected returns					Realized returns				
	CAPM	FF3	C4	FF5	HXZ4	CAPM	FF3	C4	FF5	HXZ4
1	0.09	−0.05	−0.21	−1.05	−0.98	0.56	0.65	0.79	0.57	0.75
2	0.27	0.20	0.14	−0.32	−0.25	0.57	0.54	0.65	0.56	0.55
3	0.39	0.36	0.32	0.00	0.08	0.69	0.58	0.57	0.43	0.60
4	0.49	0.48	0.46	0.23	0.32	0.63	0.61	0.63	0.65	0.67
5	0.59	0.59	0.59	0.43	0.53	0.66	0.67	0.51	0.65	0.54
6	0.70	0.71	0.72	0.63	0.73	0.67	0.65	0.65	0.68	0.62
7	0.81	0.84	0.86	0.84	0.94	0.62	0.74	0.72	0.72	0.75
8	0.95	0.99	1.03	1.09	1.20	0.70	0.88	0.85	0.65	0.74
9	1.15	1.21	1.27	1.44	1.54	0.70	0.87	0.74	0.86	0.84
10	1.56	1.71	1.82	2.19	2.36	0.71	0.70	0.78	0.79	0.77
10 – 1 spread	1.47	1.77	2.03	3.24	3.34	0.15	0.05	−0.01	0.22	0.01
t-stat	88.55	142.06	110.80	109.96	154.08	0.39	0.16	−0.04	0.92	0.05
9 – 2 spread	0.88	1.01	1.13	1.76	1.79	0.13	0.33	0.09	0.30	0.29
t-stat	104.77	157.83	131.42	115.77	220.27	0.47	1.59	0.43	1.58	1.35

Panel B: Industries

	Expected returns					Realized returns				
	CAPM	FF3	C4	FF5	HXZ4	CAPM	FF3	C4	FF5	HXZ4
1	0.43	0.43	0.38	0.17	0.01	0.75	0.68	0.56	0.57	0.54
2	0.59	0.65	0.60	0.40	0.30	0.77	0.67	0.76	0.59	0.70
3	0.67	0.78	0.72	0.53	0.46	0.66	0.92	0.82	0.78	0.75
4	0.75	0.90	0.83	0.67	0.62	0.69	0.57	0.79	0.86	0.82
5	0.90	1.10	1.03	0.88	0.86	0.70	0.88	0.76	0.81	0.88
5 – 1 spread	0.47	0.67	0.66	0.71	0.86	−0.06	0.20	0.19	0.25	0.34
t-stat	51.70	112.06	102.67	171.86	94.98	−0.22	0.97	0.89	1.27	1.73

horizon. This is consistent with the notion that risk loadings change over time. A practitioner should therefore be careful with projecting expected returns far into the future.

To obtain further insights into the relation between expected and realized returns, I sort firms into ten portfolios based on out-of-sample expected returns. The advantage of using portfolio sorts is that it exposes any non-linearities between the expected and realized returns. Table 3.10 presents value-weighted expected and realized returns for the one-month-ahead expected return sorted portfolios. Panel A shows the results for individual firms and Panel B shows the results for industries. Although the realized returns generally increase from the low to the high expected return portfolio, the increase is not monotonic. The results also show that the return spreads between the extreme portfolios ($10-1$ spread) are not significant for any model. Since the returns do not increase monotonically, I also present $9-2$ spreads. In contrast to the $10-1$ spread, all $9-2$ spreads are positive, but none are statistically significant. For industries, the conclusions are similar, except that the Hou, Xue, and Zhang (2015) four-factor model is significant (at the 10% level) with a t-statistic of 1.73. Using equal-weighted instead of value-weighted returns provides similar results. Overall, the results indicate that the forecasting ability of the five asset pricing models I examine is poor, and raise questions about their practical usefulness.

3.8 Conclusion

Considerable progress has been made in the asset pricing literature to explain the cross-section of expected returns. As a result, practitioners have a large number of asset pricing models at their disposal which they can use for applications such as capital budgeting and making investment decisions. In this paper, I show that the expected returns produced by the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model, and the Hou, Xue, and Zhang (2015) four-factor model are not particularly useful for these purposes. First, I show that the models I evaluate produce very different expected return estimates. The average range between the five rolling window expected returns is more than 19% per year for firms and almost 17% per year for industries. Second, I show that expected returns are estimated with large errors. For instance, the annualized standard errors are on average around 13% for the Fama and French (2015) and Hou, Xue, and Zhang (2015) models. Statistically, I cannot reject the hypothesis that the expected returns produced by the five models are the same for almost all firms at any period in time. I show that the expected returns are especially dissimilar during the Internet Bubble and the Global Financial Crisis, and that the standard errors of the expected return estimates are also relatively large during these periods. Third, I show that securities that are estimated to have high expected returns by these models experience high realized returns only when the estimates are precise. However, the forecast errors are substantial, even for precise estimates of expected returns.

The results have several implications. Given the large dissimilarity between the expected returns of the five popular asset pricing models I evaluate, practitioners should critically assess whether or not cost of equity or expected return estimates are sensitive to the choice of model. Moreover, practitioners should realize that the estimates have big estimation errors, thus should adjust their actions accordingly. Finally, since expected returns generally align with future realized returns when the estimates are precise, practitioners should consider estimation errors in assessing the actual usefulness of the estimates.

Overall, this paper demonstrates that the usefulness of linear factor models to estimate costs of equity capital or expected returns is limited. Future research should aim to further guide practitioners in valuing firms and investment projects. For instance, are there more precise methods to estimate expected returns? How should practitioners incorporate risk to obtain reliable estimates of project values?

Appendices

3.A Factors

Table 3.A.1. Overview of Models

The table provides an overview of all the factors in all the models considered in this paper. FF3 refers to the Fama and French (1993) three-factor model, C4 to the Carhart (1997) four-factor model (C4), FF5 to the Fama and French (2015) five-factor model, and HXZ4 to the Hou, Xue, and Zhang (2015) four-factor model.

Model	Market	Size	Value	Momentum	Profitability	Investment
CAPM	MKT					
FF3	MKT	SMB	HML			
C4	MKT	SMB	HML	MOM		
FF5	MKT	SMB (FF5)	HML		PROF (FF5)	INV (FF5)
HXZ4	MKT (HXZ4)	SMB (HXZ4)			PROF (HXZ4)	INV (HXZ4)

3.B Factor Construction

CAPM: The market factor is the value-weighted excess return on all firms listed on the NYSE, AMEX, and NASDAQ.

Fama and French (1993): The market factor is defined similarly as in the CAPM. Book equity is defined as stockholders' equity plus deferred taxes plus investment tax credit minus preferred stock redemption value. If stockholders' equity is not available, it is constructed by subtracting liabilities from total assets. The value factor is based on the market-to-book ratio. The size and value factors are based on an independent two-by-three sort on size and market-to-book. First, the median NYSE market equity is used to sort firms into two groups of small and big firms. Next, NYSE breakpoints are used to form value portfolios for which the breakpoints are based on the 30% lowest, 40% middle, and 30% highest values. The sort happens at the end of June each year. The portfolios are rebalanced monthly and returns are value weighted.

Carhart (1997): The market, size, and value factors are defined similarly as in the Fama and French (1993) three-factor model. Momentum is defined as the cumulative return from $t-12$ to $t-2$. The momentum factor is based on an independent two-by-three sort on size and momentum. The remaining steps are similar to those used to construct the book-to-market factor of Fama and French (1993).

Fama and French (2015): Size and value are measured similarly as in the Fama and French (1993) three-factor model. Profitability is measured as revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense, and the result divided by book value of equity from the end of the last fiscal year. Investments is measured as the growth in total assets from $t-2$ to $t-1$, scaled by total assets at $t-1$ from the end of the fiscal year. The value, profitability, and investment factors are based on independent two-by-three sorts on size and the respective variables. First, the median NYSE market equity is used to form groups of small and big firms. Next, NYSE breakpoints are used to form three value, profitability, and investment portfolios for which the breakpoints are based on the 30% lowest, 40% middle, and 30% highest values. The aforementioned sorts happen at the end of June each year. Based on the independent sorts, eighteen portfolios are formed. The portfolios are rebalanced monthly and returns are value weighted.

The market factor is defined similarly as in the CAPM. The size factor is defined as the average of the average returns on the six small size portfolios minus the average returns of the six big size portfolios. The value factor is defined as the average return on the two small size-value portfolios minus the returns of the two big size-value portfolios. The value factor is constructed by subtracting the average of the two high investment portfolios from that of the two low value portfolios. The profitability factor is constructed by subtracting the average return on the two low profitability portfolios from the average of the two high profitability portfolios. The investment factor is constructed by subtracting the average return on the two high investment portfolios from that of the two low investment portfolios.

Hou, Xue, and Zhang (2015): Profitability is defined as income (before extraordinary items) divided by book equity of the previous quarter. Investments is measured as the growth in total assets from $2-1$ to $t-1$, scaled by total assets at $t-2$ and measured at the fiscal year ends. The factors are based on an independent two-by-three-by-three sort on size, investment, and profitability. First, the median NYSE market equity is used to sort firms into two groups of small and big firms. Second, NYSE breakpoints are used to form three investment portfolios for which the breakpoints are based on the 30% lowest, 40% middle, and 30% highest growth in total assets. The aforementioned sorts happen at the end of June each year. Third, firms are also sorted into three portfolios for which the breakpoints are based on the 30% lowest, 40% middle, and 30% highest growth in profitability. The profitability breakpoints are redetermined every month. Based on the independent sorts, eighteen portfolios are formed.

The portfolios are rebalanced monthly and returns are value weighted.

The market factor is the value-weighted excess return on the market. The size factor is constructed by subtracting the average return on the nine small size portfolios from that on the nine big size portfolios. The investment factor is constructed by subtracting the average return on the six high investment portfolios from that on the six low investment portfolios. The profitability factor is constructed by subtracting the average return on the six low profitability portfolios from the average return on the six high profitability portfolios.

3.C Robustness Checks

Table 3.C.1. Expected Versus Realized Returns for Firms with Alternative Risk Loadings

This table presents the coefficients of Fama and MacBeth (1973) regressions of expected returns on realized returns for firms. The expected return estimates are from the CAPM, the Fama and French (1993) three-factor model (FF3), the Carhart (1997) four-factor model (C4), the Fama and French (2015) five-factor model (FF5), and the Hou, Xue, and Zhang (2015) four-factor model (HXZ4). The table presents results for four alternative estimation procedures of the risk loadings: for Vasicek (1973)-adjusted five-year rolling window risk loadings, three-year rolling window risk loadings, expanding window risk loadings, and industry risk loadings. The table shows results for one-month, one-year, and five-year-ahead forecasts, and for the full sample and three subgroups of firms. The subgroups are formed by sorting firms into three portfolios based on the standard errors of the expected return estimates, and rebalancing every month. The sample period is from January 1977 to December 2013. *, **, and *** indicate statistical significance levels of 10%, 5%, and 1%, respectively.

	Vasicek-adjusted				36 Month Rolling Window			
	Full	Low	Med	High	Full	Low	Med	High
One-month-ahead forecasts								
CAPM	0.24	0.34	0.01	−0.15	0.14	0.33**	0.03	−0.10
FF3	0.38*	0.57***	0.35**	0.32	0.22*	0.40***	0.24**	0.14
C4	0.15	0.38***	0.19	0.04	0.11	0.23**	0.18**	0.06
FF5	0.08	0.16*	0.09	0.08	0.02	0.07	0.04	0.02
HXZ4	0.04	0.15*	0.09	0.01	0.03	0.09*	0.05	0.01
One-year-ahead forecasts								
CAPM	0.16	0.11	−0.21	−0.20	0.09	0.15	−0.06	−0.14
FF3	0.29	0.42***	0.26	0.26	0.17	0.29***	0.18**	0.10
C4	0.10	0.31***	0.11	−0.02	0.08	0.20**	0.11	0.02
FF5	0.09	0.15**	0.09	0.07	0.03	0.07*	0.06	0.02
HXZ4	0.06	0.12*	0.09	0.01	0.02	0.05	0.03	0.01
Five-year-ahead forecasts								
CAPM	−0.24	0.02	−0.24	−0.27	−0.19*	0.00	−0.15	−0.20**
FF3	0.07	0.29***	0.19***	0.09	0.03	0.22***	0.09**	0.02
C4	−0.08	0.15**	0.01	−0.09	−0.04	0.11***	0.01	−0.04***
FF5	0.06	0.12***	0.05	0.06	0.03	0.08***	0.04	0.01
HXZ4	−0.02	0.04	0.03	0.01	0.00	0.04*	0.04***	0.00

	Expanding Window				Industry			
	Full	Low	Med	High	Full	Low	Med	High
One-month-ahead forecasts								
CAPM	0.15	0.28	0.08	−0.18	−0.04	0.13	−0.03	−0.03
FF3	0.28*	0.50***	0.29**	0.21*	0.15	0.34*	0.11	0.03
C4	0.11	0.33**	0.16	0.06	0.10	0.41**	0.03	−0.14
FF5	0.07	0.21**	0.09	0.07	0.09	0.14	−0.05	0.18
HXZ4	0.03	0.14	0.05	0.02	0.11	0.24*	−0.01	0.20
One-year-ahead forecasts								
CAPM	0.09	0.11	−0.10	−0.24*	−0.01	0.07	−0.28	0.20
FF3	0.24*	0.37***	0.27**	0.17	0.15	0.38	0.11	0.21
C4	0.06	0.25**	0.11	0.01	0.17	0.43**	0.00	0.12
FF5	0.07	0.18**	0.09	0.07	0.17	0.19	0.05	0.30
HXZ4	0.03	0.10	0.05	0.03	0.13	0.19	−0.02	0.23
Five-year-ahead forecasts								
CAPM	−0.16	0.03	−0.07	−0.14	−0.17	−0.05	−0.25	0.14
FF3	0.05	0.20*	0.20***	0.06	0.34*	0.26	0.24	0.47**
C4	−0.08	0.08	−0.01	−0.06*	0.16	0.15	0.02	0.31*
FF5	0.05	0.13*	0.05	0.04	0.12	0.00	0.08	0.23*
HXZ4	−0.02	0.02	0.00	0.01	0.09	0.05	0.06	0.21

Chapter 4

Understanding the Sources of Stock Price Variation*

4.1 Introduction

News about future cash flows and discount rates moves stock prices in efficient markets. An important difference between these components of stock price variation is that the former has a permanent price effect, while the latter has a transitory price effect. Negative news about cash flows results in a price drop, but leaves expected returns unchanged. Although an increase in discount rates also results in a price drop, it is associated with higher expected returns. If discount rates are stationary, which they in theory should be, then price changes due to shocks to discount rates should ultimately be reversed. It is therefore important to distinguish between these two types of news in understanding stock price variation.

For a long time the general view has been that variation in discount rates is the main source of stock price variation (Campbell, 1991; Campbell and Vuolteenaho, 2004; Cochrane, 2008). This view has been challenged by evidence showing that dividend smoothing hides the role of cash flow news (Ang and Bekaert, 2007; Larrain and Yogo, 2008; Chen, Da, and Priestley, 2012) and that the traditional decomposition method used to show that discount rate news is relatively important is unstable (Goyal and Welch, 2008; Chen and Zhao, 2009). Cash flow news is important in the long term, because it should be the main driver of stock price variation if discount rates are stationary (Vuolteenaho, 2002; Hansen, Heaton, and Li, 2008; Bansal, Dittmar, and Kiku, 2009).

The return decomposition has traditionally been examined at the market level using index returns (e.g., Campbell, 1991; Campbell and Ammer, 1993), and it has used

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the market-level components to estimate risk exposures (Campbell and Vuolteenaho, 2004). The return decomposition has also been investigated at the firm level (e.g., Vuolteenaho, 2002; Chen, Da, and Zhao, 2013), but there has been little focus on the cross-sectional heterogeneity in the importance of cash flow news versus discount rate news as drivers of stock price variation. The aim of this paper is to fill this gap.

Understanding what moves stock prices and whether and why some stocks are more sensitive to cash flow news and others to discount rate news is important in constructing theoretical asset pricing models. For instance, the time-variation in risk premia can be attributed to shocks to discount rates (e.g., Campbell and Cochrane, 1999; Ang and Liu, 2004), or to shocks to the volatility of future cash flow growth rates (e.g., Bansal and Yaron, 2004). While the discount rate channel might be more suited for discount rate news-driven stocks, the cash flow channel might be more important for cash flow news-driven stocks. Understanding the sources of stock price movements is also important for investors aiming to diversify risk. For instance, Chen, Da, and Zhao (2013) show that, at the aggregate level, cash flow news is diversified away more than discount rate news. This implies that cash flow news contains relatively more idiosyncratic risk. Understanding what drives stock price variation is therefore important, as the sources of stock price variation are informative about the extent to which adding a stock to a portfolio provides diversification benefits.

In line with recent work (e.g., Chen, Da, and Zhao, 2013), I find cash flow news to be dominant at longer horizons, but also that there is substantial time series variation in the relative importance of cash flow news versus discount rate news. In addition, I show that there is large cross-sectional heterogeneity in the relative importance of cash flow news versus discount rate news at the stock level across various investment horizons. Intuitively, firms have different strategies and risk profiles, and operate in industries that experience different shocks to expected cash flows and risks. It is therefore no surprise that the amount of cash flow news versus discount rate news is different across firms. In line with this idea, I show that the cross-section of the relative importance of the two components is associated with different stock characteristics, risks, and expected returns.

Next, I examine two applications of the stock return decomposition. First, I find that the in-sample performance of some popular state variables in predicting stock returns depends on whether those returns are driven by cash flow news or discount rate news. For example, I show that stock variance performs much better in predicting the returns of stocks that are driven by discount rate news than those driven by cash flow news, while using net equity expansion as the predictor variable yields opposite results. Second, I show that cash flow news-driven stocks exhibit more co-movement than discount rate news-driven stocks.

I follow Chen, Da, and Zhao (2013) to identify the extent to which stock prices are driven by cash flow news and discount rate news. In particular, I use analyst earnings forecasts (retrieved from IBES) to estimate expected cash flows and solve for the implied cost of capital (ICC).[1] Next, I compute cash flow news as the price change keeping discount rates constant, and discount rate news as the price change while holding expected cash flows constant.[2] I proceed by constructing portfolios based on the fraction of return variance driven by cash flow news versus discount rate news. On the one extreme, the cash flow news-driven portfolio contains stocks with returns that are predominantly driven by cash flow news. On the other extreme, the discount rate news-driven portfolio contains stocks with returns that are predominantly driven by discount rate news. I compute the return decomposition for investment horizons ranging from one quarter to 28 quarters.

I show that the relative importance of the sources of stock price variation has changed over time as cash flow news explains increasingly more of the variation in stock prices. At the one quarter investment horizon, the mean fraction of capital gain return variation that is driven by cash flow news has increased from roughly 20% in 1990 to 25% in 2015. At the investment horizon of 28 quarters, this mean fraction has grown from roughly 50% in 1996 to 75% in 2015. I also find that there is

[1] There is a major concern about the quality of analyst forecasts (e.g., Abarbanell, 1992; Ali, Klein, and Rosenfeld, 1992; Francis and Philbrick, 1993; Dugar and Nathan, 1995; McNichols and O'Brien, 1997; Hayes, 1998; Lin and McNichols, 1998; Easton and Monahan, 2005; Jackson, 2005; Easton and Sommers, 2007; Hou, van Dijk, and Zhang, 2012). Chen, Da, and Zhao (2013) find that their approach is robust to biases in analyst forecasts. Moreover, they obtain similar conclusions when using the alternative VAR method instead of analyst forecasts.

[2] Other studies using this method include Khimich (2017) and Mao and Wei (2017).

substantial variation in the relative importance of cash flow news versus discount rate news across industries and individual stocks. For instance, I show that commodity-related industries are predominantly driven by cash flow news, while discount rate news is relatively more important for financial industries. I find that firms with cash flow news-driven stock returns are less profitable, invest more aggressively, have lower leverage, and are less likely to pay dividends than firms with discount rate news-driven stock returns. They also have relatively large market betas and a tilt towards small and growth stocks, while firms with stock returns driven by discount rate news have relatively low market betas and a tilt towards big and value stocks. Thus, my evidence suggests that the sources of stock price variation are related to firm fundamentals and risks.

Assuming that discount rates are stationary, stocks that are predominantly driven by discount rate news are not likely to experience large price changes in the long run. This means that when long-horizon realized returns are positive, most of the returns are likely to be driven by positive cash flow news. In line with this hypothesis, I show that firms with stock price variation that is predominantly driven by cash flow news offer higher stock returns, although this relation is statistically weak. The return differences between the portfolio mostly driven by cash flow news and the portfolio mostly driven by discount rate news are positive and statistically significant or close to being statistically significant at most investment horizons. The corresponding premia range from 1.90% to 4.85% per year. Given that the return decomposition portfolios are exposed to different risks, I also estimate risk-adjusted returns. The alpha spreads with respect to the Fama and French (2015) risk factors are large and range between 2.53% and 5.55% per year. The spreads with respect to the Fama and French (1993) risk factors and the CAPM market factor, however, are often much smaller and often statistically insignificant. Thus, my evidence suggests that the exposures to systematic risk factors play an important role in determining the size of the return spreads.

The pricing results are closely related to, but different from, Campbell and Vuolteenaho (2004). They decompose the market beta into a cash flow beta that captures return covariation with aggregate cash flow news, and a discount rate beta that captures return covariation with aggregate discount rate news. They show that the resulting two-beta model is a significant improvement over the CAPM. While this is evidence suggesting that the sources of stock price variation are important as systematic risk factors, my results show that they are important as firm-specific characteristics. In particular, while Campbell and Vuolteenaho (2004) use risk exposures to examine whether cash flow news and discount rate news are related to expected returns, I use the relative importance of the sources of stock price variation to do this.

I proceed by showing that cash flow news and discount rate news are related to the predictability of the equity premium and co-movement in stock returns. From July 1989 to December 2015, stock variance, net equity expansion, the dividend yield, and the dividend-price ratio are significant in-sample predictors of the equity premium. I show that the predictive power of stock variance comes mostly from stocks that have return variation predominantly driven by discount rate news. The predictive power of net equity expansion is much weaker, but it is generally driven by stocks that have return variation predominantly driven by cash flow news. The predictive power of the dividend yield and the dividend-price ratio is related to both types of stocks. The results also show that the returns of discount rate news-driven stocks exhibit more co-movement than those of cash flow news-driven stocks. This effect, although economically small, points to the greater importance of the common fundamental factors behind discount rates than behind cash flows.

In conclusion, understanding the cross-sectional heterogeneity in the relative importance of the sources of stock price variation is instrumental as it provides fresh insights into some central themes in asset pricing.

4.2 Stock Return Decomposition

In this subsection, I provide summary statistics on the implied cost of capital (ICC) and the return decomposition at the firm, industry, and aggregate levels. I also examine the variation in the relative importance of the return components over time.

Table 4.1. Summary Statistics of the Implied Cost of Capital

This table presents summary statistics on the implied cost of capital (ICC). The ICC is estimated every quarter based on the most recent quarterly analyst earnings forecasts (from IBES). For every year from 1985 to 2015, the table reports the average across quarters of the number of stocks in the sample, the mean and median market value, select percentiles (25%, median, and 75%), as well as the cross-sectional standard deviation (StDev) of the ICC. Market values are expressed in millions of dollars and the ICC values are expressed in percentages.

		Market Value		ICC			
Year	Nr. Stocks	Mean	Median	25%	Median	75%	StDev
1985	1,631	951	246	13.9	15.7	18.0	3.6
1986	1,616	1,229	282	11.9	13.7	15.8	3.3
1987	1,696	1,407	297	11.7	13.7	16.0	3.6
1988	1,666	1,336	290	12.6	14.5	16.7	3.5
1989	1,718	1,531	307	11.9	13.8	15.8	3.4
1990	1,723	1,566	272	12.6	14.7	17.3	3.9
1991	1,722	1,759	322	11.7	13.4	15.6	3.2
1992	1,875	1,860	355	11.5	13.3	15.5	3.2
1993	2,150	1,930	381	11.5	13.3	15.6	3.4
1994	2,520	1,835	324	12.0	13.8	16.2	3.6
1995	2,719	2,069	367	11.9	14.0	16.2	3.4
1996	2,978	2,438	401	11.7	13.8	16.4	3.8
1997	3,295	2,923	467	11.4	13.9	16.9	4.2
1998	3,284	3,546	460	11.6	14.6	17.8	4.6
1999	3,089	4,584	471	11.7	14.4	17.8	4.7
2000	2,797	6,148	628	12.0	14.8	18.1	4.9
2001	2,342	5,738	735	11.3	13.5	16.6	4.6
2002	2,258	5,214	751	11.0	12.8	15.1	3.6
2003	2,428	5,393	865	10.1	11.7	13.6	2.9
2004	2,558	6,352	1,086	9.7	11.4	13.1	3.0
2005	2,617	6,676	1,193	9.8	11.3	13.1	3.0
2006	2,612	7,418	1,282	9.8	11.5	13.3	3.2
2007	2,547	8,509	1,407	10.1	11.6	13.4	2.9
2008	2,398	6,968	1,067	11.2	13.2	15.7	4.2
2009	1,988	6,371	1,102	9.8	11.6	13.8	4.1
2010	2,149	7,680	1,487	9.8	11.6	13.7	3.7
2011	2,240	8,037	1,624	10.4	12.4	14.7	4.1
2012	2,129	9,212	1,898	9.8	11.8	14.0	3.9
2013	1,995	11,989	2,610	8.9	10.7	12.7	3.6
2014	2,005	13,978	3,062	9.0	10.8	13.0	3.8
2015	1,917	14,591	3,249	8.8	10.5	12.8	3.9

4.2.1 Computing the ICC

The ICC is the rate by which expected future cash flows are discounted such that it equals the current stock price. The computation of the ICC closely follows the literature (e.g., Pastor, Sinha, and Swaminathan, 2008; Lee, Ng, and Swaminathan, 2009; Chen, Da, and Zhao, 2013) and is described in Appendix 4.A.

I report the summary statistics of the ICC from 1985 to 2015 in Table 4.1. The summary statistics closely resemble those reported in Chen, Da, and Zhao (2013). The sample starts in 1985 due to limited IBES coverage before that year. The number of stocks in the sample increases from 1,631 in 1985 to 3,295 in 1997, and thereafter decreases to 1,917 in 2015. The mean (median) market value increases steadily from \$951 (\$246) million in 1985 to \$14,591 (\$3,249) million in 2015. The select percentiles (25%, median, and 75%) of the ICC distribution indicate that the ICC estimates decreased over time. The median discount rate was 15.7% in 1985 and decreased to only 10.5% in 2015. The general trend is downward, with sporadic upward swings. For example, in 2008 the median ICC was 13.2%, while in the year before and the year after it was 1.6% lower at 11.6%. The downward trend suggests that stocks experienced an upward pressure in prices as expected cash flows became less heavily discounted over time. This is not necessarily surprising because interest rates also decreased over the sample period (e.g., Levi and Welch, 2014). The cross-sectional distribution of the ICC is tight and varies over time between 2.9% and 4.9%.

4.2.2 Cash Flow News and Discount Rate News

The decomposition of returns into a cash flow news component and a discount rate news component follows Chen, Da, and Zhao (2013). The decomposition is based on capital gain returns. The capital gain return on a stock is its simple return minus its dividend return. As pointed out by Chen, Da, and Zhao (2013), the role of dividends is not likely to change any conclusions as their role in total return volatility is small. The two components reflect the price change if an investor had only updated her information about future cash flows or discount rates. I use the decomposition to infer how much of the variation in capital gain returns is attributable to variation in the individual components. Appendix 4.B provides further details on the decomposition method.

The decomposition method I employ is different from the predictive method used in, among others, Campbell (1991), Vuolteenaho (2002), and Campbell and Vuolteenaho (2004), because it does not rely on a vector autoregressive (VAR) model to decompose stock returns. Using predictive regressions to determine the importance of the two news components is problematic because the results are sensitive to the choice of predictors and sample period (Goyal and Welch, 2008; Chen and Zhao, 2009; Maio and Philip, 2015). Nevertheless, Chen, Da, and Zhao (2013) show that the decomposition results are robust to the choice of method.[3]

Table 4.2 presents the number of firms in the sample, the median variances of capital gain return, its cash flow news component, and its discount rate news component, the mean correlation coefficient between the return components, and the mean, cross-sectional standard deviation, along with select quantiles of the fraction indicating the importance of cash flow news relative to discount rate news. Results are reported for capital gain returns based on changes in expected cash flows ranging from one quarter to 28 quarters into the future.[4] It is natural to look at various investment horizons as the relative importance of discount rate news should decline over time if discount rates are stationary.

The results are in line with Chen, Da, and Zhao (2013). The total number of stocks in the sample is $4,909$ at the one-quarter investment horizon, and decreases to $2,221$ at the 28-quarter investment horizon. The reason the sample size decreases in tandem with the investment horizon is due to the requirements on the time period of analyst forecast data that is needed to calculate the return decomposition. At the one-quarter investment horizon, the mean fraction of variation in prices that is driven by cash flow news is only 23%. At the four-quarter investment horizon, this number increases to 52%. It then grows quickly to a stable level slightly above 70%. Thus, the results show that cash flow news is more important than discount rate news in the long term. When discount rates are stationary, long-term returns should be predominantly driven by cash flow news because price drops due to increases in discount rates will be compensated for by higher future returns.

The results also indicate that there is large variation between firms as to the importance of cash flow news relative to discount rate news. The cross-sectional

[3]Alternative methods to decompose stock returns are available, such as the revisions in analysts' forecasts method of Easton and Monahan (2005). See Khimich (2017) for a comparison between various decomposition methods. Yet another approach to decompose stock returns would be to compute discount rates using an asset pricing model, and use the implied discount rates to obtain expected cash flow estimates. However, estimates of the cost of equity capital provided by these models are notoriously imprecise (Fama and French, 1997; Pastor and Stambaugh, 1999). An advantage of the method of Chen, Da, and Zhao (2013) is that it connects the news components to various investment horizons in a simple, intuitive way.

[4]For investment horizons longer than one quarter, the estimates are based on overlapping data. Chen, Da, and Zhao (2013) point out that, because the regressions are not predictive, the use of overlapping data in the regressions does not lead to biased results.

Table 4.2. Stock Return Decomposition

This table presents the return decomposition results. The number of stocks represents those that have at least sixteen return observations. The table shows the median capital gain return variance ($Var(Retx)$), cash flow news variance ($Var(Retx^{CF})$), and discount rate news variance ($Var(Retx^{DR})$), and the mean correlation coefficient between the two news components ($Cor(Retx^{CF}, Retx^{DR})$). In addition, the table shows the mean, cross-sectional standard deviation (StDev), and select percentiles (5%, 25%, median, 75%, and 95%) of the fraction of capital gain return variation that is driven by cash flow news (CF) estimated over the full sample period. Results are for investment horizons from one quarter to 28 quarters. The sample period is from 1985:Q1 to 2015:Q4.

	Investment Horizon								
	1	2	4	8	12	16	20	24	28
Nr. Stocks	4,909	4,673	4,279	3,685	3,301	2,961	2,673	2,438	2,221
$Var(Retx)$	0.04	0.07	0.14	0.28	0.42	0.55	0.75	0.87	0.96
$Var(Retx^{CF})$	0.06	0.11	0.22	0.41	0.58	0.73	0.86	0.96	1.05
$Var(Retx^{DR})$	0.08	0.14	0.23	0.32	0.40	0.46	0.53	0.56	0.61
$Cor(Retx^{CF}, Retx^{DR})$	−0.69	−0.66	−0.59	−0.51	−0.46	−0.41	−0.37	−0.33	−0.32
Distribution CF:									
Mean	0.23	0.36	0.52	0.67	0.72	0.72	0.74	0.73	0.71
StDev	0.45	0.58	0.74	0.72	0.61	0.62	0.58	0.87	0.58
5%	−0.24	−0.18	−0.14	−0.04	−0.06	−0.03	0.00	−0.01	−0.04
25%	0.06	0.15	0.26	0.40	0.44	0.47	0.48	0.49	0.48
50%	0.21	0.33	0.47	0.62	0.68	0.70	0.71	0.71	0.70
75%	0.38	0.53	0.71	0.87	0.92	0.94	0.94	0.94	0.94
95%	0.77	1.01	1.31	1.54	1.62	1.60	1.55	1.54	1.50

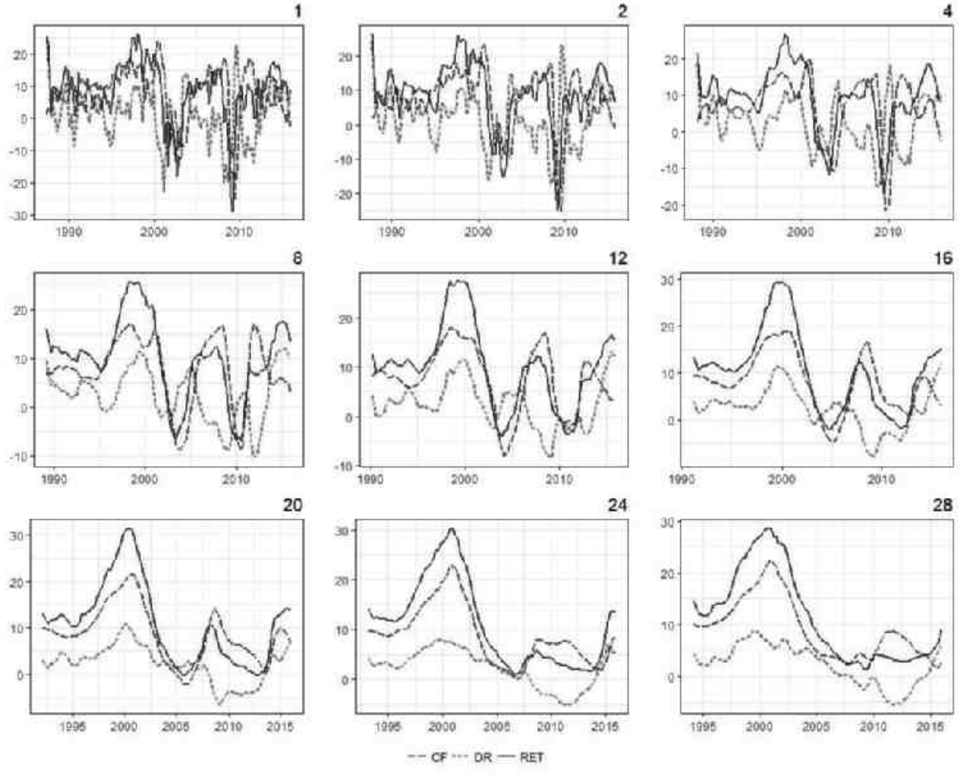
standard deviation ranges between 0.45 and 0.87 across investment horizons, which indicates that some stocks are predominantly driven by cash flow news while others are driven by discount rate news. The large distribution is also reflected in the percentiles that show that 90% of the observations are between −0.24 (5% percentile) and 0.77 (95% percentile) at the one-quarter investment horizon, and between −0.04 (5% percentile) and 1.50 (95% percentile) at the 28-quarter investment horizon. A negative fraction indicates that returns tend to decrease as positive cash flow news arrives, implying that investors increase discount rates at the same time. A fraction above one indicates that a drop in returns due to negative cash flow news tends to coincide with a drop in discount rates. I explore the cross-sectional heterogeneity in this fraction in the next section.

Price movements might be predominantly driven by shocks to cash flows during certain periods and by discount rates in others. Figure 4.1 shows the full and decomposed returns aggregated to the market level using value-weighting over several investment horizons. I plot an exponential moving average with a decay ratio of 20% to aid visual inspection. It is clearly visible that cash flow news and discount rate news add up to total market returns, especially at longer investment horizons. At the short horizons, the collapse of the Internet Bubble and the Global Financial Crisis are clearly identifiable events. Both components contributed to the drop in prices during these crisis periods. Firms saw their future prospects diminish, which resulted in drops in expected cash flows. Investors also increased discount rates, which might be due to an increase in risk aversion and a drop in expected consumption growth (Campbell and Cochrane, 1999). In line with the results in Table 4.2, the figure shows that while cash flow news and discount rate news contribute about equally to capital gain returns at short horizons of up to four quarters, at longer horizons cash flow news is the principal contributor.

The predominantly positive long-horizon returns from 1989 to 2015 can primarily be explained by upward revisions in expected cash flows. These upward revisions are most substantial around 2000, and have been relatively minor since then. The cash flow news component of market returns is positive over the sample period, which

Figure 4.1. Aggregated Return Decomposition

This figure shows exponential moving averages of full and decomposed annualized returns aggregated to the market level. The ICC is estimated every quarter based on the most recent quarterly analyst earnings forecasts (from IBES). The returns are value-weighted and based on capital gains ranging from one quarter to 28 quarters. I use a decay ratio of 20%. All the returns are in percentages.



suggests that investors increase their expectations of future earnings over time. This is intuitive, because increases in future earnings also reflect expected economic growth and inflation. The subfigures corresponding to longer investment horizons show that, after 2000, the slope of the cash flow news component is negative, suggesting that investors decreased their expectations about growth in long-term expected cash flows.

The results in Figure 4.1 show that shocks to discount rates have played a relatively minor role at long investment horizons. This is consistent with the notion that price variation should ultimately be driven by cash flow news if discount rates are stationary. At the beginning of the sample, the return component driven by discount rate news is positive, suggesting that market returns experienced an upward pressure due to decreases in discount rates. The results corresponding to longer investment horizons show that downward revisions in discount rates contributed positively to returns until approximately 2010. After that, the discount rate news component of aggregated returns turns negative. This suggests that investors started to discount future cash flows more heavily, resulting in a downward pressure on stock prices.

4.2.3 Industry Return Decomposition

In this subsection, I examine the decomposition at the industry level to obtain further insights into the heterogeneity in the importance of cash flow news relative to discount rate news. For each industry, I calculate the median of the firm-level measures of the relative importance of the two news components at all the investment horizons that I consider, as well as the cross-sectional average across these investment horizons.

Table 4.3 presents the results based on Kenneth French's industry classification.[5] I sort industries based on the average value across investment horizons.[6] Industries for which cash flow news is relatively important include the coal (Coal), precious metals (Gold), and non-metallic and industrial metal mining (Mines) industries, with average ratios across investment horizons of 1.21, 0.87, and 0.76, respectively.

[5] I thank Kenneth French for making the data available. The data can be found at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html.

[6] To examine whether the relative classification is stable across horizons, I estimate Spearman rank correlations. Unreported results show that they are positive and statistically significant.

Table 4.3. Industry Return Decomposition

This table presents the return decomposition results per industry. I use Kenneth French's industry classification. The table shows the time series average of the cross-sectional median of the fraction of capital gain return variation that is driven by cash flow news for select horizons. The average values across the reported investment horizons are also shown. I require at least five observations within an industry to be available at every time period. The start date ranges from July 1990 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

	Investment Horizon									
	1	2	4	8	12	16	20	24	28	Avg.
Coal	0.43	0.35	0.42	0.93	1.53	2.33	2.50	–	–	1.21
Gold	0.14	0.39	0.90	0.72	0.74	0.82	1.34	1.09	1.72	0.87
Mines	0.27	0.43	0.69	0.82	0.93	0.89	0.93	0.97	0.93	0.76
Oil	0.29	0.47	0.63	0.81	0.97	0.77	0.74	0.85	0.79	0.70
Chips	0.25	0.38	0.52	0.66	0.76	0.76	0.78	0.86	0.86	0.65
Cnstr	0.18	0.32	0.54	0.67	0.75	0.86	0.77	0.80	0.92	0.64
Mach	0.27	0.39	0.53	0.70	0.77	0.81	0.81	0.77	0.73	0.64
Comps	0.22	0.36	0.49	0.63	0.76	0.84	0.80	0.80	0.79	0.63
Rubbr	0.23	0.35	0.42	0.66	0.74	0.79	0.78	0.81	0.85	0.63
Fun	0.24	0.35	0.49	0.73	0.75	0.69	0.74	0.77	0.82	0.62
LabEq	0.21	0.31	0.48	0.62	0.74	0.73	0.78	0.82	0.81	0.61
Guns	0.27	0.31	0.48	0.60	0.66	0.75	0.77	0.85	0.78	0.61
Beer	0.24	0.41	0.52	0.65	0.65	0.66	0.73	0.78	0.82	0.61
Toys	0.27	0.37	0.49	0.66	0.71	0.78	0.71	0.79	0.64	0.60
Txtls	0.18	0.29	0.45	0.55	0.65	0.75	0.80	0.82	0.84	0.59
Aero	0.22	0.36	0.42	0.55	0.63	0.79	0.77	0.76	0.82	0.59
Steel	0.19	0.31	0.44	0.62	0.66	0.71	0.76	0.78	0.75	0.58
MedEq	0.20	0.35	0.48	0.61	0.73	0.74	0.68	0.71	0.65	0.57
Smoke	0.26	0.41	0.41	0.56	0.69	0.59	0.88	0.77	–	0.57
BusSv	0.20	0.31	0.45	0.63	0.70	0.75	0.72	0.68	0.68	0.57
Books	0.24	0.35	0.41	0.64	0.67	0.66	0.68	0.74	0.71	0.57
Whlsl	0.23	0.31	0.42	0.62	0.67	0.69	0.70	0.72	0.69	0.56
ElcEq	0.18	0.35	0.47	0.54	0.61	0.65	0.71	0.76	0.72	0.55
Hlth	0.18	0.25	0.37	0.56	0.69	0.72	0.64	0.75	0.79	0.55
Paper	0.23	0.37	0.41	0.53	0.62	0.64	0.68	0.69	0.72	0.54
Meals	0.17	0.26	0.38	0.52	0.66	0.70	0.73	0.71	0.66	0.53
Chems	0.20	0.35	0.42	0.56	0.63	0.64	0.67	0.67	0.65	0.53
Autos	0.24	0.32	0.39	0.55	0.63	0.64	0.65	0.69	0.66	0.53
Food	0.17	0.30	0.40	0.53	0.59	0.63	0.71	0.72	0.71	0.53
Trans	0.16	0.23	0.37	0.57	0.66	0.68	0.75	0.69	0.61	0.52
Fin	0.17	0.28	0.41	0.54	0.60	0.63	0.69	0.70	0.66	0.52
BldMt	0.21	0.31	0.41	0.52	0.59	0.64	0.65	0.67	0.65	0.52
Rtail	0.18	0.30	0.41	0.56	0.62	0.63	0.63	0.63	0.64	0.51
Clths	0.17	0.28	0.38	0.53	0.61	0.63	0.65	0.66	0.64	0.51
Hshld	0.17	0.31	0.38	0.53	0.60	0.65	0.67	0.64	0.61	0.51
Drugs	0.13	0.29	0.43	0.55	0.60	0.64	0.65	0.64	0.60	0.50
RlEst	0.22	0.28	0.51	0.55	0.64	0.67	0.65	–	–	0.50
Other	0.14	0.29	0.40	0.50	0.60	0.64	0.71	0.57	0.53	0.49
FabPr	0.30	0.27	0.49	0.59	–	0.74	0.54	–	–	0.49
PerSv	0.14	0.26	0.33	0.50	0.62	0.66	0.64	0.62	0.61	0.49
Soda	0.17	0.29	0.33	0.45	0.51	0.56	0.65	0.67	0.67	0.48
Boxes	0.28	0.35	0.35	0.38	0.57	0.51	0.59	0.63	0.65	0.48
Banks	0.18	0.25	0.34	0.44	0.48	0.52	0.59	0.64	0.60	0.45
Insur	0.14	0.20	0.29	0.40	0.51	0.56	0.60	0.60	0.61	0.43
Telcm	0.08	0.23	0.27	0.44	0.51	0.53	0.50	0.61	0.51	0.41
Ships	0.26	0.47	0.29	–	–	–	–	–	–	0.34
Util	0.11	0.16	0.19	0.30	0.39	0.40	0.46	0.53	0.47	0.33

These industries are all related to commodities. Thus, for these industries, changes in investor's expectations of future returns have a relatively small effect on prices. Industries for which discount rate news is relatively important include the utilities (Util) and shipbuilding and railroad equipment (Ships) industries, with average ratios of 0.33 and 0.34, respectively. With average ratios of 0.43, 0.45, and 0.52, discount rate news also plays a relatively important role for financial industries such as the insurance (Insur), banking (Banks), and trading (Fin) industries, respectively. These results show that there is considerable cross-sectional heterogeneity in the relative importance of the return components at the industry level.

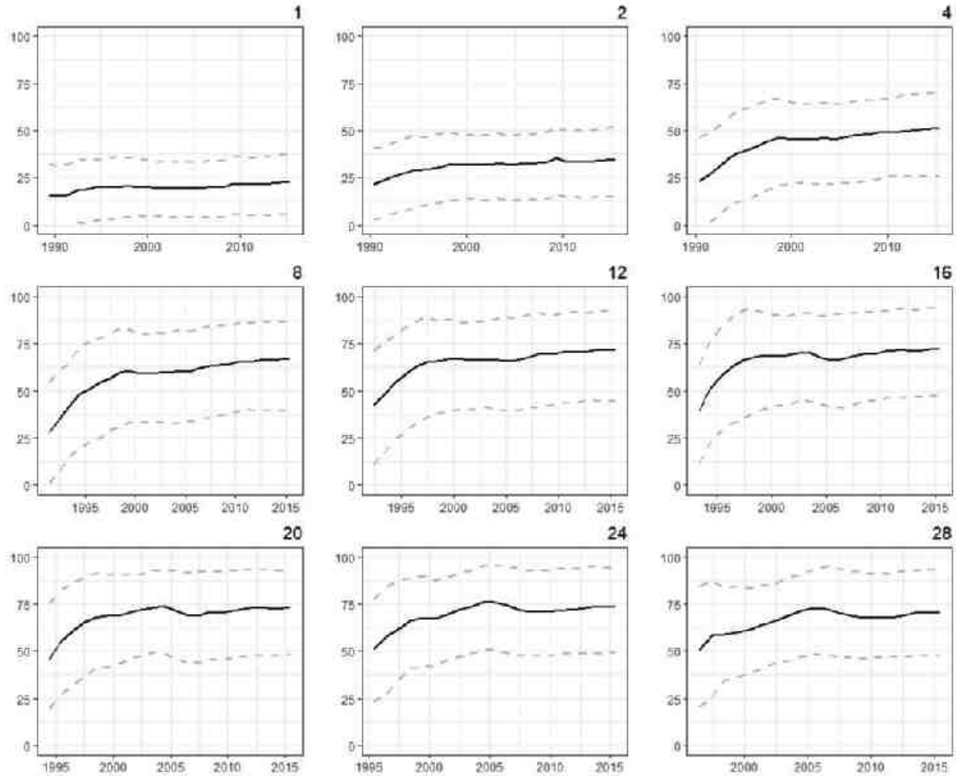
4.2.4 Time Series Variation in the Importance of the Sources of Stock Price Variation

In this subsection, I examine whether any deductions regarding the importance of cash flow news relative to discount rate news have changed over time. The importance of cash flow news might have increased since cash flows have become more correlated as a result of globalization, market integration, and global pricing. In addition, it has become easier for young and small firms to become publicly listed. As a result, it might be that cash flow news appears to be the main driver of stock price variation due to the idiosyncratic nature of these young and small firms.

To examine the time series variation in the sources of stock price variation, I calculate the stock price decomposition over time, using only data that are available up to the date of estimation. Figure 4.2 illustrates that cash flow news has become more important. There is a general increase in the fraction of stock price variation driven by cash flow news over time across all investment horizons. The biggest increase in this measure occurred before 2000. The quantiles indicate that the cross-sectional distribution is stable over time. Clearly, the decomposition at different time periods gives different pictures of the relative importance of the two components of stock price variation. In line with the results in Table 4.2, the results shown in the figure also confirm that the fraction of price variation driven by cash flow news increases with investment horizon.

Figure 4.2. Time Series Variation of Contribution of Return Components

This figure shows the time series evolution on the fraction of capital gain return variation that is driven by cash flow news. For several horizons, the solid line represents the mean, and the dashed lines below and above it denote the 25% and 75% percentiles, respectively. The decomposition is estimated over time, and I require at least sixteen observations to be available to calculate the decomposition. The time series averages and percentiles are calculated if at least 100 stock observations are available. All the numbers are in percentages. The start date ranges from July 1989 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.



4.3 Return Decomposition Portfolios

To minimize the effect of estimation error in the return components, I construct portfolios based on the relative importance of cash flow news versus discount rate news (see Blume, 1970). In particular, I sort stocks as of the end of June of each year into five portfolios based on the fraction in historical capital gain returns that is driven by cash flow news. The decomposition is computed based on data in real time.[7] I sort the data for investment horizons ranging from one quarter to 28 quarters. I use these portfolios to study how cash flow news and discount rate news are related to firm characteristics, risks, and expected returns, as well as to study the predictability of the equity premium and stock return co-movement.

4.3.1 Properties of Return Decomposition Portfolios

In this subsection I examine whether the stocks in the return decomposition portfolios differ in their characteristics and risk exposures. Table 4.4 presents statistics on the following portfolio characteristics: the fraction of capital gain return variation that is driven by cash flow news (the sorting variable), size, book-to-market ratio, profitability, investment, leverage, and dividends. Appendix 4.C provides details on how the variables are constructed.

By construction, the stocks in the portfolios differ in the extent to which the two components are responsible for stock price variation. On the one hand, the mean fractions corresponding to the extreme discount rate news-driven portfolios range from −19.3% to 13.4% across investment horizons, suggesting that variation in discount rates is the main source of price variation of stocks in those portfolios. On the other hand, the mean fractions corresponding to the extreme cash flow news portfolios range from 65.5% to 137.8% across investment horizons, confirming that most of the price variation of the stocks in these portfolios is driven by cash flow

[7] Thus, the decomposition used to construct the portfolios is based on an expanding window. I also consider the possibility that the relative importance of the sources of stock price variation changes over time and compute the decomposition based on a rolling window of various lengths. I also try constructing portfolios with fixed breakpoints at 20%, 40%, 60%, and 80%. A major drawback of using fixed breakpoints is that the number of stocks in the portfolios varies substantially over time. In addition, the discount rate news-driven portfolios contain most stocks at short horizons, while the cash flow news-driven portfolios contain most stocks at long horizons. The main conclusions do not change with these alternative specifications.

Table 4.4. Characteristics of Return Decomposition Portfolios

Stocks are sorted into five portfolios as of the end of June of each year based on the fraction of capital gain return variation that is driven by cash flow news. The results are for investment horizons ranging from one quarter to 28 quarters. For each horizon and portfolio, the table shows the time series average of the mean fraction of variation in historical capital gain returns that is driven by cash flow news (the sorting variable), the median market capitalization (size), book-to-market ratio, profitability, investment, leverage, and the mean dividend dummy. Market values are expressed in millions of dollars and the other variables are expressed in percentages. The start date ranges from July 1990 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

		Investment Horizon								
	Pf	1	2	4	8	12	16	20	24	28
CF	DR	−19.3	−12.7	−9.7	−1.3	5.4	7.2	10.9	13.4	9.0
	2	7.3	16.9	24.3	36.6	44.0	47.2	49.6	51.8	49.7
	3	19.0	30.0	40.9	54.9	62.7	65.4	67.1	68.7	66.8
	4	31.4	44.3	58.5	73.7	81.9	84.4	85.2	86.2	84.4
	CF	65.5	83.4	108.5	129.7	137.8	136.6	135.5	134.7	129.9
Size	DR	932	1,033	1,143	1,307	1,413	1,537	1,663	1,831	1,786
	2	1,259	1,445	1,685	1,814	2,047	2,224	2,453	2,606	2,920
	3	1,193	1,332	1,365	1,585	1,760	2,309	2,444	2,740	2,881
	4	1,089	1,099	1,065	1,311	1,545	1,698	2,166	2,370	2,883
	CF	734	772	876	1,101	1,322	1,360	1,311	1,425	1,688
BM	DR	63.9	75.4	66.7	65.7	62.9	63.9	62.0	60.7	63.9
	2	52.4	49.3	47.2	46.8	49.8	47.9	47.6	46.2	47.3
	3	48.9	46.9	49.9	49.7	46.8	45.6	46.0	45.5	43.3
	4	50.8	47.6	53.3	45.1	44.0	46.4	46.0	49.8	43.2
	CF	67.8	62.3	55.0	59.5	59.1	56.4	54.7	50.3	50.6
Profitability	DR	36.4	37.1	38.9	37.8	39.0	39.4	42.0	41.3	39.3
	2	39.1	37.9	38.5	38.2	37.2	38.1	37.0	37.0	40.3
	3	38.1	39.1	37.8	39.1	40.2	39.4	38.0	39.1	37.8
	4	37.4	36.6	38.0	40.8	41.3	42.0	43.8	41.1	39.8
	CF	33.1	36.0	34.6	32.9	32.1	33.8	34.8	38.6	40.2
Investment	DR	10.5	10.4	9.9	9.3	9.8	9.0	8.5	9.0	9.0
	2	11.1	10.4	10.5	10.6	10.0	10.2	10.1	10.2	10.0
	3	10.1	10.2	10.5	9.8	9.3	9.4	10.6	9.2	9.2
	4	11.0	11.3	10.9	9.8	9.3	9.7	9.2	9.5	9.7
	CF	13.0	12.4	12.6	13.4	12.1	11.8	11.1	11.8	11.5
Leverage	DR	129.0	120.2	102.5	109.3	127.2	105.3	110.4	101.2	97.8
	2	117.3	120.5	132.1	139.0	129.4	137.0	140.2	128.6	118.1
	3	83.1	127.0	124.3	110.2	114.7	129.5	127.9	148.4	167.8
	4	111.9	98.6	99.1	103.9	92.6	97.4	94.7	115.3	111.2
	CF	115.8	82.2	82.3	82.7	84.5	81.1	83.3	84.9	87.6
Div. dummy	DR	87.2	85.9	89.0	91.5	88.9	88.9	87.3	88.1	89.0
	2	87.7	89.6	91.3	87.8	89.8	89.7	88.4	89.0	91.2
	3	86.2	88.9	86.0	89.0	88.9	89.0	88.9	90.3	90.2
	4	84.5	81.4	79.3	84.9	84.8	85.9	90.0	89.1	90.2
	CF	75.2	73.5	76.5	71.4	75.8	78.0	80.3	83.5	83.6

news. Clearly, the separation is not perfect as a minor part of price variation of the stocks in the cash flow news-driven (discount rate news-driven) portfolios is still driven by discount rate (cash flow) news.

At each investment horizon, the extreme cash flow news-driven portfolio contains the smallest stocks, and the extreme discount rate news-driven portfolio generally contains slightly larger stocks. The stocks in the portfolios in-between are generally larger than those in the extreme portfolios. The observation that size increases with investment horizon is due to the different samples of stocks. The sample is smaller at longer horizons due to the extensive time period of analyst forecast data required to calculate the return decomposition. As a result, average stock size increases with investment horizon as many small stocks are excluded from the sample. A similar U-shape is also visible for the book-to-market ratio. The ratio is highest for the most discount rate news-driven portfolios, followed by the most cash flow news-driven portfolios.

Firms in the discount rate news-driven portfolios are generally more profitable, invest less, have more leverage, and are more likely to pay dividends than firms in the cash flow news-driven portfolios. These results are in line with those in Table 4.3. For instance, the characteristics corresponding to firms with discount rate news-driven stocks, such as being profitable and highly leveraged, are also typically associated with financial industries. Thus, firms that differ in their relative importance of the drivers of stock price variation are different in their characteristics.[8]

The finding that firms with high leverage are primarily driven by discount rate news is intuitive, because both leverage and discount rates are positively related to changes in interest rates. The economic channels through which the other characteristics are connected to the two types of news, however, are more complex. For instance, investments might be linked to both components. Investors might update their expectations about future cash flows when investments are made, as well as their expectations about discount rates if investments are made in projects that change the risk profile of the firm. The extent to which firm characteristics are related to

[8]The difference in characteristics between the extreme portfolios $(5-1)$ are all highly statistically significant.

the two news components is therefore an empirical question.

To test whether the portfolios have different risks, I compute risk loadings with respect to the market, size, value, profitability, and investment factors of the Fama and French (2015) five-factor model. I estimate the risk loadings based on value-weighted portfolio returns. The results in Table 4.5 show clear differences between the market, size, and value betas across all horizons, as well as in the profitability and investment betas across horizons up to twenty quarters. In particular, the cash flow news-driven portfolios have more market risk than the discount rate news-driven portfolios. The cash flow news-driven portfolios have a tilt towards small and growth stocks while the discount rate news-driven portfolios have a tilt towards big and value stocks. The finding that the size betas of the extreme portfolios differ is consistent with the idea that small stocks, which usually have less well-diversified investment projects, have more variation in expected cash flows than big stocks. The expected cash flows of big stocks are relatively stable, suggesting that their returns are predominantly driven by variation in discount rates. The spread in value betas reflects differences in the stability of cash flows. Growth stocks have more variation in expected cash flows while value stocks have relatively stable cash flows, suggesting that variation in discount rates is a more important driver of stock price variation. The discount rate news-driven portfolios have a tilt towards strong profitably and aggressive investment, while the cash flow news-driven portfolios have a tilt towards weak profitability and conservative investment. The profitability and investment tilts are in line with the pattern in the corresponding characteristics in Table 4.4. The patterns in the size and value betas, however, do not correspond to the U-shape of the corresponding characteristics.

A related question is whether the return decomposition portfolios are exposed to risks that are specifically related to the return components. In particular, Campbell and Vuolteenaho (2004) present a model in which they decompose the market beta into a cash flow beta and a discount rate beta. The cash flow beta measures an asset's sensitivity to market cash flow news while the discount rate beta measures an asset's sensitivity to market discount rate news. However, their decomposition of the

Table 4.5. Risk Exposures of Return Decomposition Portfolios

Stocks are sorted into five portfolios as of the end of June of each year based on the fraction of capital gain return variation that is driven by cash flow news. The results are for investment horizons ranging from one quarter to 28 quarters. For each horizon and portfolio, the table shows the post-ranking betas with respect to the five Fama-French factors. The betas are estimated by regressing the full sample time series of value-weighted portfolio excess returns on the five factors in multivariate regressions. Spreads in betas between the extreme portfolios (5 – 1 spread) and corresponding t-statistics adjusted for heteroscedasticity and autocorrelations are also reported. The start date ranges from July 1990 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

		Investment Horizon								
	Pf	1	2	4	8	12	16	20	24	28
MKT beta	DR	0.99	0.95	0.92	0.90	0.93	0.90	0.92	0.88	0.90
	2	0.96	0.95	0.95	0.95	0.95	0.96	0.93	0.92	0.89
	3	0.94	1.01	1.04	1.01	0.99	0.97	1.02	1.04	1.01
	4	1.05	1.03	1.05	1.08	1.07	1.07	1.05	1.09	1.09
	CF	1.16	1.11	1.11	1.05	1.08	1.10	1.08	1.07	1.04
	5 – 1	0.17	0.16	0.19	0.15	0.15	0.20	0.17	0.19	0.15
	t-stat	4.89	2.98	4.05	2.88	3.34	4.22	3.86	3.48	3.01
SMB beta	DR	−0.11	−0.08	−0.09	−0.17	−0.13	−0.08	−0.06	−0.09	−0.12
	2	−0.21	−0.14	−0.19	−0.17	−0.24	−0.19	−0.24	−0.26	−0.16
	3	−0.10	−0.11	−0.08	−0.15	−0.12	−0.20	−0.24	−0.16	−0.23
	4	0.02	−0.08	−0.02	0.02	−0.03	−0.05	−0.04	−0.06	−0.07
	CF	0.12	0.06	0.05	0.19	0.22	0.21	0.22	0.06	0.04
	5 – 1	0.23	0.14	0.14	0.36	0.35	0.29	0.28	0.15	0.16
	t-stat	4.21	1.69	1.92	4.20	4.40	3.54	3.69	1.74	2.39
HML beta	DR	0.11	0.30	0.15	0.17	0.24	0.14	0.11	0.15	0.15
	2	0.04	−0.01	0.09	0.11	0.13	0.21	0.13	0.13	0.18
	3	0.01	0.03	0.06	0.07	0.11	0.06	0.22	0.20	0.17
	4	0.07	0.02	−0.05	−0.13	−0.15	−0.15	−0.12	−0.01	−0.03
	CF	−0.07	−0.18	−0.12	−0.04	−0.04	−0.04	−0.10	−0.17	−0.19
	5 – 1	−0.18	−0.48	−0.27	−0.22	−0.27	−0.18	−0.21	−0.32	−0.34
	t-stat	−1.90	−3.50	−2.66	−2.27	−2.44	−1.88	−3.01	−3.33	−4.58
RMW beta	DR	0.06	0.05	0.23	0.16	0.19	0.26	0.30	0.15	0.16
	2	0.19	0.09	0.05	0.12	0.05	0.07	0.13	0.17	0.31
	3	0.13	0.24	0.13	0.16	0.13	0.04	0.04	0.16	0.06
	4	0.04	−0.02	0.14	0.02	0.22	0.23	0.15	0.21	0.18
	CF	−0.10	−0.07	−0.11	0.00	0.03	0.11	0.21	0.20	0.24
	5 – 1	−0.16	−0.13	−0.34	−0.16	−0.17	−0.15	−0.09	0.05	0.08
	t-stat	−2.31	−1.31	−2.86	−1.23	−1.69	−1.58	−0.94	0.63	0.75
CMA beta	DR	0.21	0.06	0.20	0.18	0.08	0.12	0.21	0.09	0.11
	2	0.23	0.10	0.03	0.11	0.07	0.12	0.28	0.28	0.18
	3	−0.07	0.21	0.07	0.13	0.10	0.17	−0.11	0.14	0.09
	4	−0.05	−0.20	0.00	−0.01	0.16	0.13	0.35	0.17	0.27
	CF	−0.17	−0.06	−0.20	−0.21	−0.09	−0.12	−0.02	0.13	0.16
	5 – 1	−0.39	−0.12	−0.39	−0.40	−0.17	−0.24	−0.23	0.05	0.05
	t-stat	−3.30	−0.65	−2.70	−2.82	−1.31	−2.04	−1.93	0.32	0.43

Table 4.6. Cash Flow and Discount Rate Betas of Return Decomposition Portfolios

Stocks are sorted into five portfolios as of the end of June of each year based on the fraction of capital gain return variation that is driven by cash flow news. The results are for investment horizons ranging from one quarter to 28 quarters. For each horizon and portfolio, the table shows the CAPM beta, the cash flow and discount rate beta of Campbell and Vuolteenaho (2004), and the cash flow beta as a percentage of the CAPM beta (in percentage points). I also report the spreads in betas between the extreme portfolios (5 – 1 spread). The start date ranges from July 1990 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

		Investment Horizon								
	Pf	1	2	4	8	12	16	20	24	28
CAPM beta	DR	0.89	0.86	0.77	0.76	0.79	0.75	0.75	0.77	0.77
	2	0.82	0.87	0.87	0.84	0.84	0.84	0.77	0.74	0.69
	3	0.89	0.86	0.96	0.89	0.88	0.88	0.94	0.90	0.90
	4	1.03	1.04	0.99	1.07	0.96	0.96	0.93	0.96	0.95
	CF	1.24	1.16	1.19	1.11	1.12	1.10	1.05	0.99	0.95
	5 – 1	0.34	0.30	0.42	0.35	0.33	0.35	0.30	0.22	0.17
CF beta	DR	0.25	0.24	0.21	0.21	0.22	0.20	0.20	0.20	0.21
	2	0.22	0.25	0.25	0.25	0.24	0.24	0.21	0.20	0.19
	3	0.25	0.24	0.27	0.25	0.24	0.24	0.26	0.25	0.26
	4	0.30	0.29	0.27	0.30	0.27	0.28	0.26	0.27	0.27
	CF	0.36	0.33	0.33	0.30	0.31	0.30	0.29	0.27	0.25
	5 – 1	0.11	0.09	0.12	0.10	0.08	0.10	0.10	0.07	0.04
DR beta	DR	0.65	0.62	0.56	0.55	0.57	0.55	0.55	0.56	0.56
	2	0.60	0.62	0.62	0.59	0.61	0.60	0.56	0.55	0.51
	3	0.64	0.62	0.69	0.64	0.64	0.63	0.68	0.65	0.65
	4	0.73	0.74	0.72	0.77	0.69	0.68	0.67	0.68	0.67
	CF	0.88	0.85	0.87	0.82	0.81	0.80	0.76	0.72	0.70
	5 – 1	0.23	0.23	0.32	0.27	0.24	0.25	0.21	0.16	0.14
CF beta (%)	DR	27.9	27.9	27.4	27.0	28.0	26.6	26.6	26.6	26.9
	2	27.2	28.8	29.1	29.7	28.1	28.6	27.7	26.6	26.9
	3	28.2	27.7	27.9	28.0	27.2	27.7	27.2	27.6	28.5
	4	28.9	28.3	27.8	28.2	28.1	28.9	28.2	28.5	28.8
	CF	28.8	28.3	27.5	27.2	27.4	27.1	28.1	27.4	26.5
	5 – 1	31.3	29.4	27.7	27.7	26.0	28.3	31.9	29.9	24.5

market beta does not explain why the return decomposition portfolios are exposed to other risk factors, as portrayed by the results in Table 4.5.

Table 4.6 reports the CAPM, the cash flow, and the discount rate betas for the five return decomposition portfolios. The return component betas are based on the fitted values of the two market news components based on a VAR model that is similar to the one used by Campbell and Vuolteenaho (2004). Further computation details are in Appendix 4.D. I also present the 5 – 1 beta spreads and ratios of cash flow beta to total market beta.

Consistent with the results in Table 4.5, the portfolios containing cash flow news-driven stocks have higher market betas than the portfolios containing discount rate news-driven stocks. The difference ranges between 0.17 and 0.42 across investment horizons. The portfolios containing cash flow news-driven stocks have both higher cash flow risk and discount rate risk. The $5-1$ differences between cash flow betas range from 0.04 to 0.12, and the differences between discount rate betas range from 0.14 to 0.32 across investment horizons. The cash flow beta is a constant fraction, generally around 30%, of the CAPM beta across portfolios and investment horizons. Thus, the absolute beta values, and not the relative magnitudes in risks, are different across the return decomposition portfolios. This suggests that the two-beta model cannot be discriminated from the single-beta CAPM (Campbell and Vuolteenaho, 2004). These results, however, should be interpreted with caution. Chen and Zhao (2009) show that the cash flow and discount rate betas are highly sensitive to model specification, and that opposite conclusions are easily reached with alternative state variables.

Overall, the results show that there is considerable heterogeneity among stocks in the importance of the two components of stock price variation. The portfolios based on the relative importance of these two components have different fundamentals and exposures to common risk factors. These results lead to the question of whether expected returns differ between the different types of stocks.

4.3.2 Relation to the Cross-Section of Expected Returns

In this subsection, I examine the differences between the average returns of stocks that are mostly driven by cash flow news and the average returns of stocks that are mostly driven by discount rate news. Table 4.7 presents the portfolio excess returns, alphas with respect to the CAPM, the Fama and French (1993) three-factor model, and the Fama and French (2015) five-factor model, spreads between the returns on the extreme portfolios ($5-1$ spreads), and corresponding t-statistics.[9]

The results in Table 4.7 suggest that the importance of cash flow news relative to

[9] I follow the approach in Shumway (1997) to avoid survivorship bias in the stock returns. In particular, I use the delisting return on CRSP. If it is missing, I assign a return of −30% if the reason for deletion is related to performance. The corresponding deletion codes are 500 (reason unavailable), 520 (went to OTC), 551-573 and 580 (various reasons), 574 (bankruptcy), and 584 (does not meet exchange financial guidelines). In all other cases, I assume a delisting return of zero.

Table 4.7. Pricing of Return Decomposition Portfolios

Stocks are sorted into five portfolios as of the end of June of each year based on the fraction of capital gain return variation that is driven by cash flow news. The results are for investment horizons ranging from one quarter to 28 quarters. For each horizon, the table reports annualized average portfolio returns and annualized one-, three-, and five-factor alphas. The alphas are with respect to the CAPM and the factors of Fama and French (1993) and Fama and French (2015). The alphas are the intercepts of full sample regressions of value-weighted portfolio excess returns on the factors. The table also reports the spreads in excess returns and five-factor alphas between the extreme portfolios (5 – 1 spread) and corresponding t-statistics adjusted for heteroscedasticity and autocorrelations. The start date ranges from July 1990 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

		Investment Horizon								
	Pf	1	2	4	8	12	16	20	24	28
Excess returns	DR	7.60	6.09	7.30	6.70	6.11	7.22	8.47	5.98	4.73
	2	7.35	7.86	6.69	7.27	6.73	6.29	6.62	6.80	6.00
	3	8.06	7.70	7.61	7.04	8.15	7.02	6.94	7.13	6.97
	4	8.20	8.08	8.24	8.70	7.70	8.82	8.39	8.53	6.62
	CF	9.50	10.33	10.17	11.54	10.67	10.75	11.84	9.94	8.63
	5 – 1	1.90	4.23	2.86	4.85	4.56	3.53	3.37	3.96	3.90
	t-stat	0.92	1.82	1.04	1.85	1.90	1.52	1.55	1.98	1.82
1-Factor Alphas	DR	0.95	−0.43	1.48	0.76	−0.03	1.57	2.54	0.26	−0.59
	2	1.21	1.29	0.10	0.68	0.15	−0.04	0.49	1.25	1.19
	3	1.40	1.18	0.36	0.03	1.35	0.43	−0.56	0.44	0.76
	4	0.56	0.24	0.75	0.33	0.28	1.58	1.01	1.39	0.08
	CF	0.33	1.61	1.25	2.96	2.14	2.57	3.61	2.64	2.16
	5 – 1	−0.61	2.04	−0.24	2.20	2.17	1.01	1.07	2.38	2.75
	t-stat	−0.33	0.90	−0.09	0.95	0.94	0.51	0.54	1.26	1.27
3-Factor Alphas	DR	0.33	−1.60	0.54	−0.11	−0.91	0.91	1.82	−0.31	−1.20
	2	0.80	1.25	−0.11	0.20	−0.14	−0.68	−0.12	0.65	0.36
	3	1.45	0.67	0.03	−0.34	0.89	0.20	−0.87	−0.26	0.36
	4	0.38	0.59	0.86	0.81	0.48	1.76	0.84	1.14	−0.25
	CF	0.75	2.37	2.03	3.25	2.09	2.53	3.58	2.77	2.33
	5 – 1	0.43	3.97	1.49	3.36	2.99	1.61	1.76	3.08	3.53
	t-stat	0.29	1.98	0.67	1.47	1.52	0.85	0.97	1.75	1.85
5-Factor Alphas	DR	−0.69	−2.10	−1.36	−1.59	−2.29	−1.02	−0.67	−1.48	−2.45
	2	−0.94	0.44	−0.52	−0.88	−0.72	−1.50	−1.76	−1.31	−1.96
	3	0.94	−1.34	−0.89	−1.65	−0.20	−0.61	−0.73	−1.67	−0.26
	4	0.31	1.27	0.05	0.73	−1.28	−0.01	−1.23	−0.71	−2.15
	CF	1.83	2.99	3.23	3.96	2.26	2.24	2.39	1.11	0.47
	5 – 1	2.53	5.09	4.59	5.55	4.55	3.26	3.06	2.60	2.92
	t-stat	1.65	2.37	2.21	2.39	2.17	1.60	1.46	1.53	1.43

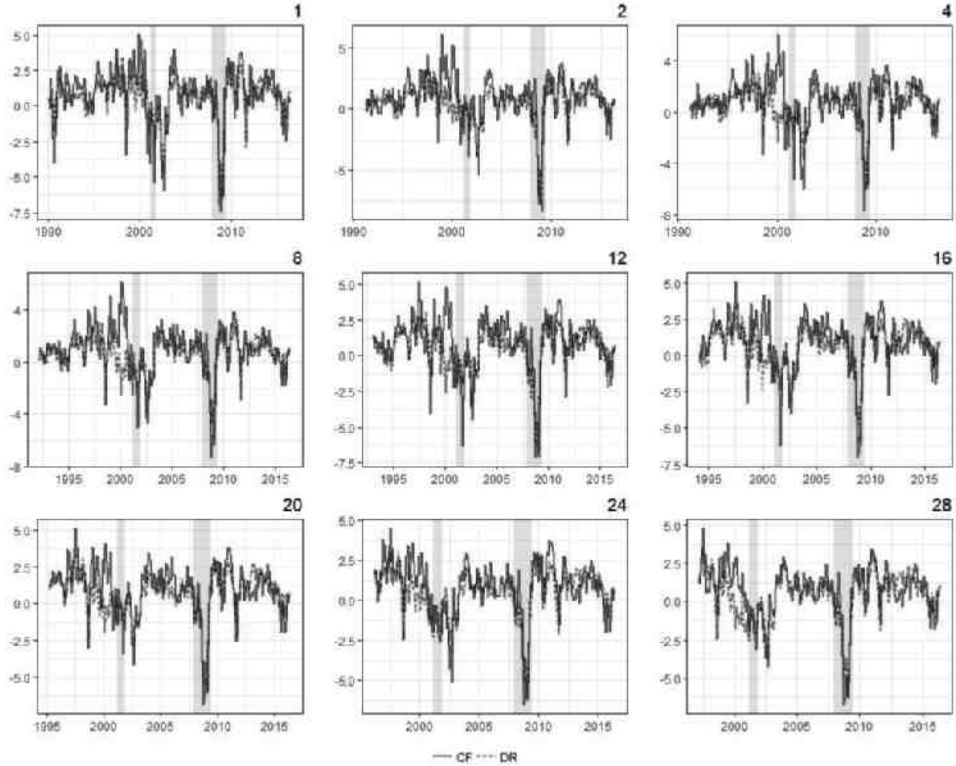
discount rate news is related to expected returns. For each horizon, the return spread between the extreme portfolios is positive. The spreads are statistically significant or close to being statistically significant at the two-, eight-, twelve-, 24-, and 28-quarter investment horizons. Although these results are statistically weak, the spreads are economically large as they range from 1.90% to 4.85% on a yearly basis. The excess returns show either a monotonic increase or a close to monotonic increase from the discount rate news-driven portfolio to the cash flow news-driven portfolio across all horizons. Thus, the results suggest that the more variation in capital gain returns is driven by cash flow news, the greater the expected excess return offered to investors. This is in line with the idea that if discount rates are stationary, then returns should be driven by cash flow news in the long run.

Since the results in Table 4.5 show that the return decomposition portfolios differ on their exposures to systematic risk factors, I calculate risk-adjusted portfolio returns. Table 4.7 shows the one-, three-, and five-factor alphas of each portfolio, the alpha spreads between the extreme portfolios, and corresponding t-statistics. The results show that the CAPM alphas are not significantly different from zero and that the signs are not uniformly positive across investment horizons. However, only controlling for exposure to market risk might not be sufficient because Table 4.5 indicates that the return decomposition portfolios have different exposures to risk factors. When controlling for additional risk factors, I find that the cash flow news-driven portfolios offer higher returns than the discount rate news-driven portfolios. This is consistent with the results based on the excess return spreads. The corresponding alpha spreads are positive at all investment horizons and range from 0.43% to 3.97% per year for the Fama and French (1993) three-factor model and from 2.53% to 5.55% per year for the Fama and French (2015) five-factor model. The spreads of both models are statistically significant at most investment horizons.

The explanation for the large risk-adjusted return spreads based on the Fama and French (2015) factors is that the cash flow news-driven portfolios generally have negative exposures to the profitability and investment factors, suggesting that they hedge against profitability and investment risks, while the exposures of the discount

Figure 4.3. Time Series Variation in Portfolio Returns

This figure shows exponential moving averages of the excess returns of the bottom and top portfolios where stocks are sorted on the fraction of capital gain return variation that is driven by cash flow news. The results are for investment horizons ranging from one quarter to 28 quarters. The start date ranges from July 1989 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015. The decay ratio is 20%. All the returns are in percentages. The shaded areas indicate periods of NBER-defined recessions.



rate news-driven portfolios are generally positive. Controlling for these exposures therefore increases the spreads between the extreme portfolios.

In contrast to the results based on excess returns, however, the alphas do generally not increase monotonically from the discount rate news-driven portfolios to the cash flow news-driven portfolios. The results indicate that the alpha spreads are generally generated by the high alphas of the portfolios that are mostly driven by cash flow news.

To examine how the portfolio returns behave and whether or not the reported spreads are realized steadily over time, I plot the excess returns of the two extreme portfolios over time. Figure 4.3 shows that, across all investment horizons, the excess returns are highly correlated. This is not necessarily surprising, because the positive correlations are partly driven by imperfect separation of the sources of stock price variation. As shown in Table 4.4, the cash flow news-driven stocks and discount rate news-driven stocks are still partly driven by discount rate news and cash flow news, respectively. Two NBER-defined recessions took place during the sample period, namely the collapse of the Internet Bubble and the Global Financial Crisis. The excess stock returns driven by cash flow news are often higher outside recessionary periods.[10] This is in line with the idea that the returns of discount rate news-driven stocks are bounded due to the stationarity of discount rates.

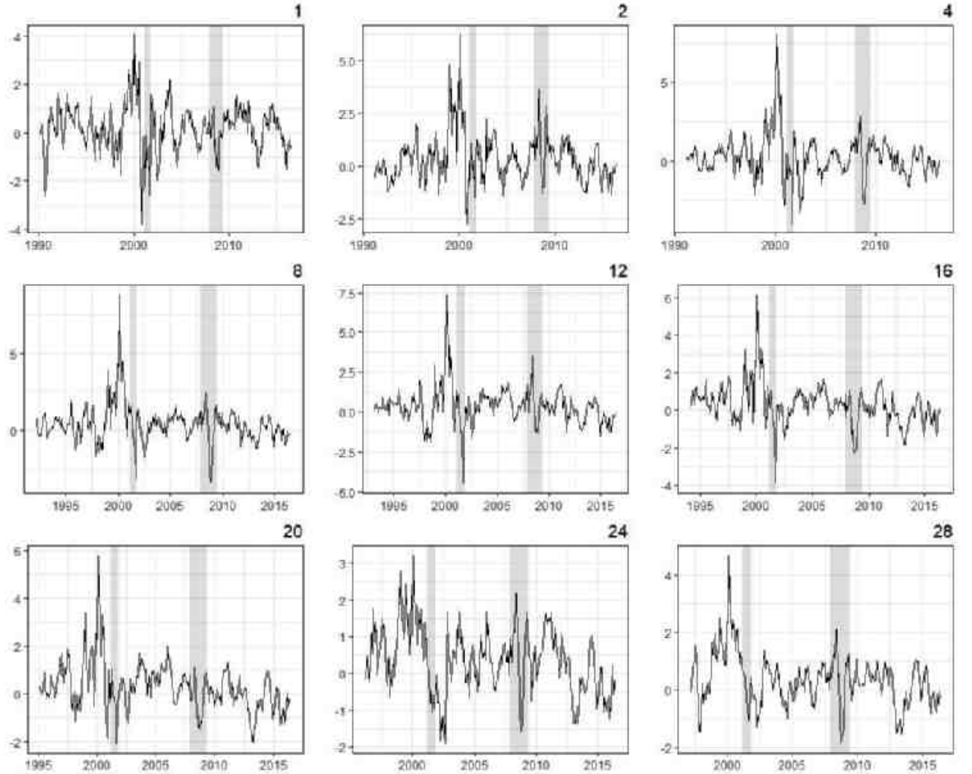
To illustrate the differences in portfolio returns more clearly, I plot the time series evolution of the 5 – 1 spread between the portfolio excess returns. Figure 4.4 shows that the two recessions are characterized by differences in the relative importance of cash flow news versus discount rate news. During the collapse of the Internet Bubble, the spread between the excess returns increased. This means that discount rate news-driven stocks reacted more than cash flow news-driven stocks. This result is consistent with the results in Figure 4.1, which show that investors heavily increased short-term discount rates during the Internet Bubble. In contrast, at the peak of the Global Financial Crisis, the return spread experienced a large negative shock, indicating that revisions in expected cash flows played a more important role than revisions in discount rates. This finding also corresponds to the results in Figure 4.1, which show that the largest decrease in returns due to declines in expected cash flows happened at the same time.

If discount rates are indeed stationary, then the returns of discount rate news-driven stocks should be stationary, too. If they are, this might provide insights into why the Jegadeesh (1990) short-term reversal strategy is profitable. To test this hypothesis, I examine the profitability of a return reversal strategy based on the two return components. This strategy is closely related to, but different from, Da, Liu, and Schaumburg (2014), who find that a short-term reversal strategy based on

[10] The pricing results remain qualitatively similar when excluding recession periods.

Figure 4.4. Time Series Variation in Portfolio Spreads

This figure shows exponential moving averages of the return difference (5 − 1 spreads) of portfolios where stocks are sorted on the fraction of capital gain return variation that is driven by cash flow news. The results are for investment horizons ranging from one quarter to 28 quarters. The start date ranges from July 1989 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015. The decay ratio is 20%. All the returns are in percentages. The shaded areas indicate periods of NBER-defined recessions.



news unrelated to firm fundamentals significantly enhances its profitability. Their approach is different from the one I take because their reversal strategy is based on a different decomposition. In particular, they define news unrelated to firm fundamentals as the stock return minus cash flow news and minus the expected return from the Fama and French (1993) three-factor model. Thus, they decompose stock returns into three components. In contrast, I do not decompose discount rate news further into an expected return component and a non-fundamental return component.

I construct portfolios by separately sorting on the two return components. First, I sort stocks into five portfolios based on the cash flow news component at the end of each quarter. Second, I sort stocks into five portfolios based on the discount rate news component. Next, I hold on to the portfolios for one, two, and three months after rebalancing each quarter. The idea is that news might arrive after the rebalancing moments, which may impact the order of the stocks. Therefore, the results based on short-term holding periods are more "clean" in the sense that they better reveal any short-term reversal effects. When no stocks are included in a portfolio, I assume that the investment grows at the risk-free rate.

Table 4.8 presents statistics on the sorting variable and portfolio returns. The table reports the $5 - 1$ spreads between the extreme portfolios and corresponding t-statistics. For a one-month holding period, the discount rate news reversal strategy achieves a negative spread ranging from -4.41% to -12.40% across investment horizons. This spread is significant at all investment horizons except those for one and eight quarters. This suggests that there is substantial mean reversion in prices after a discount rate shock and points to the transitory nature of discount rates. In contrast, the cash flow news reversal strategy is associated with insignificant spreads at all investment horizons. This suggests that cash flow shocks have a permanent price impact because the cash flow news component of returns does not reverse. For strategies based on longer holding periods, the portfolio spreads and corresponding significance levels diminish. For instance, for the two-month holding period, all spreads are still negative, but only statistically significant (at the 5% level) at the twelve-, 20-, and 28-quarter investment horizons. For the three-month holding pe-

Table 4.8. Return Reversal Portfolios

Stocks are sorted into five portfolios based on the two components of realized capital gain returns at the end of each quarter. In particular, one sort is based on the return component that is driven by cash flow news ($\boldsymbol{Retx^{CF}}$) and the other is based on the return component that is driven by discount rate news ($\boldsymbol{Retx^{DR}}$). The table reports results for investment horizons ranging from one quarter to 28 quarters. For each horizon, the table reports the $5-1$ spread in the cash flow and discount rate news components of historical capital gain returns (the sorting variable), portfolio return spreads based on three trading strategies, and corresponding t-statistics adjusted for heteroscedasticity and autocorrelations. The trading strategies are based on holding the portfolio for one month, two months, or three months (i.e., the entire quarter) after the formation date. All returns are annualized. The start date ranges from July 1990 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

	Investment Horizon								
	1	2	4	8	12	16	20	24	28
Sorting Variable Statistics									
$\boldsymbol{Retx^{CF}}$	2.94	2.19	1.63	1.17	0.96	0.86	0.79	0.74	0.71
t-stat	31.68	21.55	15.58	13.72	16.06	11.43	8.64	8.05	8.65
$\boldsymbol{Retx^{DR}}$	3.32	2.26	1.51	0.95	0.71	0.59	0.51	0.45	0.42
t-stat	32.68	21.70	14.09	11.97	13.51	12.59	10.68	11.14	11.19
One-Month Holding Period									
$\boldsymbol{Retx^{CF}}$	1.91	1.30	−1.49	0.47	0.01	0.71	0.75	−1.75	5.30
t-stat	0.49	0.32	−0.34	0.10	0.00	0.14	0.16	−0.38	1.14
$\boldsymbol{Retx^{DR}}$	−4.41	−11.66	−9.57	−6.63	−8.43	−8.45	−8.56	−10.31	−12.40
t-stat	−1.21	−2.81	−2.34	−1.54	−2.21	−2.38	−2.16	−2.14	−3.02
Two-Month Holding Period									
$\boldsymbol{Retx^{CF}}$	0.30	−0.82	−3.13	−3.77	−0.14	−1.70	−0.77	−1.88	−1.23
t-stat	0.12	−0.28	−1.01	−1.18	−0.05	−0.50	−0.24	−0.56	−0.36
$\boldsymbol{Retx^{DR}}$	−2.78	−5.66	−2.08	−2.21	−7.02	−3.61	−5.79	−5.91	−4.92
t-stat	−1.01	−1.70	−0.62	−0.76	−2.75	−1.42	−2.21	−1.99	−1.86
Three-Month Holding Period									
$\boldsymbol{Retx^{CF}}$	1.54	1.70	−1.23	−1.90	0.32	−1.53	−0.68	−2.40	−2.02
t-stat	0.77	0.72	−0.48	−0.76	0.12	−0.58	−0.26	−0.90	−0.76
$\boldsymbol{Retx^{DR}}$	1.35	−0.33	4.22	2.54	−2.26	−0.64	−2.04	−1.92	−0.94
t-stat	0.59	−0.13	1.55	1.09	−1.02	−0.30	−0.98	−0.87	−0.44

riod, however, none of the spreads are statistically significant. This is consistent with the idea that news arrives after the rebalancing moments, making it more difficult to separate out any reversal effects.

In sum, I present suggestive evidence that the cross-section in the relative importance of cash flow news versus discount rate news is associated with expected returns. Stocks that are predominantly driven by cash flow news offer higher returns than stocks that are predominantly driven by discount rate news.

4.3.3 Portfolio Stability Across Time and Investment Horizons

In this subsection, I examine whether the relative importance of the sources of stock price variation at the stock level varies across horizons. I do this to address the question of whether short-term cash flow news-driven stocks and discount rate news-driven stocks are similarly classified in the long term. I also investigate whether the relative importance of the drivers of stock price variation varies over time to assess the stability of the decomposition.

Table 4.9 shows the cross-sectional portfolio transition probabilities for select investment horizons. The persistence is generally high. For instance, for all cash flow news-driven (discount rate news-driven) stocks that are classified as such at the one-quarter investment horizon, as many as 46%, 34%, and 33% (51%, 38%, and 34%) are similarly classified at the four-, sixteen-, and 28-quarter investment horizons, respectively. The probability of switching between extreme portfolios is modest. Indeed, the probability of these stocks being classified as discount rate news-driven (cash flow news-driven) at the four-, sixteen-, and 28-quarter investment horizons is only 9%, 13%, and 15% (4%, 11%, and 14%), respectively. The results suggest that the allocation to portfolios is relatively stable across investment horizons.

Table 4.10 shows the cross-sectional averages of the time series portfolio transition probabilities based on stocks that have at least ten years of data. The persistence in portfolio allocation is generally high and the pattern in transition probabilities is consistent across investment horizons. At the one quarter investment horizon, the probability of remaining in the same portfolio in the next period is 63% for cash flow news-driven stocks and 83% for discount rate news-driven stocks. At the 28-quarter

Table 4.9. Cross-Sectional Portfolio Transition Probabilities

Stocks are sorted into five portfolios as of the end of June of each year based on the fraction of capital gain return variation that is driven by cash flow news. I compute the full-sample decomposition for investment horizons ranging from one quarter to 28 quarters. I discard firms that are not covered by all investment horizons. The sample includes 2,008 firms. This table presents the transition probabilities from portfolios for select horizons (one, four, sixteen, and 28 quarters). The sample period is from 1985:Q1 to 2015:Q4.

		4 Quarters					16 Quarters					28 Quarters				
		DR	2	3	4	CF	DR	2	3	4	CF	DR	2	3	4	CF
1 Quarter	DR	0.46	0.24	0.12	0.09	0.09	0.34	0.20	0.18	0.14	0.13	0.33	0.18	0.19	0.14	0.15
	2	0.30	0.29	0.18	0.15	0.07	0.26	0.24	0.20	0.21	0.09	0.23	0.25	0.25	0.16	0.11
	3	0.14	0.25	0.30	0.20	0.12	0.16	0.25	0.23	0.22	0.14	0.15	0.25	0.21	0.22	0.17
	4	0.06	0.16	0.27	0.30	0.21	0.13	0.17	0.21	0.24	0.25	0.15	0.17	0.19	0.26	0.22
	CF	0.04	0.07	0.12	0.26	0.51	0.11	0.14	0.18	0.18	0.38	0.14	0.15	0.16	0.21	0.34
4 Quarters	DR						0.51	0.25	0.13	0.07	0.05	0.46	0.22	0.16	0.10	0.06
	2						0.23	0.33	0.22	0.15	0.07	0.21	0.27	0.26	0.16	0.11
	3						0.13	0.22	0.29	0.24	0.13	0.13	0.24	0.25	0.24	0.14
	4						0.07	0.13	0.27	0.31	0.22	0.11	0.17	0.23	0.27	0.21
	CF						0.06	0.07	0.10	0.22	0.54	0.09	0.09	0.12	0.23	0.47
16 Quarters	DR											0.60	0.23	0.08	0.04	0.05
	2											0.18	0.36	0.30	0.11	0.06
	3											0.09	0.21	0.37	0.24	0.08
	4											0.06	0.12	0.18	0.38	0.25
	CF											0.06	0.08	0.08	0.23	0.55

Table 4.10. Time Series Portfolio Transition Probabilities

Stocks are sorted into five portfolios as of the end of June of each year based on the fraction of capital gain return variation that is driven by cash flow news. I do this for investment horizons ranging from one quarter to 28 quarters. This table presents the cross-sectional averages of the time series portfolio transition probabilities for select horizons. For each stock, I require at least ten years of data to compute the time series transition matrix. The start date ranges from July 1990 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

	DR	2	3	4	CF	DR	2	3	4	CF
	1 Quarter					16 Quarters				
DR	0.83	0.09	0.02	0.01	0.05	0.82	0.11	0.02	0.01	0.04
2	0.11	0.57	0.26	0.03	0.03	0.11	0.55	0.27	0.04	0.02
3	0.04	0.08	0.60	0.25	0.03	0.04	0.10	0.55	0.27	0.03
4	0.05	0.03	0.08	0.59	0.25	0.04	0.03	0.11	0.57	0.25
CF	0.13	0.04	0.05	0.15	0.63	0.10	0.03	0.04	0.17	0.65
	2 Quarters					20 Quarters				
DR	0.83	0.10	0.02	0.01	0.04	0.81	0.11	0.02	0.02	0.05
2	0.11	0.57	0.27	0.03	0.03	0.13	0.53	0.29	0.03	0.03
3	0.04	0.08	0.59	0.26	0.03	0.04	0.11	0.56	0.25	0.04
4	0.04	0.03	0.08	0.59	0.25	0.04	0.03	0.12	0.54	0.27
CF	0.12	0.04	0.05	0.14	0.65	0.10	0.03	0.05	0.17	0.65
	4 Quarters					24 Quarters				
DR	0.83	0.10	0.01	0.01	0.04	0.80	0.12	0.02	0.02	0.05
2	0.11	0.57	0.27	0.03	0.03	0.14	0.53	0.27	0.04	0.03
3	0.03	0.08	0.60	0.26	0.03	0.04	0.11	0.54	0.28	0.03
4	0.04	0.03	0.08	0.60	0.25	0.04	0.03	0.13	0.53	0.27
CF	0.11	0.04	0.05	0.15	0.66	0.10	0.03	0.05	0.18	0.64
	8 Quarters					28 Quarters				
DR	0.82	0.11	0.02	0.01	0.04	0.78	0.13	0.02	0.01	0.05
2	0.11	0.56	0.27	0.03	0.02	0.13	0.53	0.28	0.03	0.02
3	0.04	0.09	0.58	0.26	0.04	0.04	0.10	0.54	0.28	0.04
4	0.04	0.03	0.09	0.60	0.25	0.03	0.03	0.12	0.54	0.27
CF	0.10	0.04	0.04	0.15	0.67	0.11	0.03	0.05	0.17	0.65
	12 Quarters									
DR	0.82	0.11	0.02	0.01	0.04					
2	0.11	0.56	0.27	0.03	0.02					
3	0.04	0.10	0.57	0.26	0.04					
4	0.04	0.03	0.10	0.59	0.24					
CF	0.10	0.03	0.04	0.17	0.66					

investment horizon, the probability of remaining in the same portfolio the next period is 65% for cash flow news-driven stocks and 78% for discount rate news-driven stocks. The higher persistence for discount rate news-driven stock suggests that they are less likely to be allocated to another portfolio than cash flow news-driven stocks. Thus, in addition to being stable in the cross-sectional dimension, the portfolio allocation is also fairly stable in the time series dimension.

4.4 Predictability of the Equity Premium

There is a vast literature on the question of whether the equity premium is predictable. Goyal and Welch (2008) review this literature and examine a large number of predictive variables that have been proposed. They conclude that the predictive models are generally unstable and perform poorly, especially late in their sample (see also Chen and Zhao, 2009; Maio and Philip, 2015). Nevertheless, Cochrane (2008) argues that either discount rates or cash flows must be forecastable to explain the observed variation in dividend-price ratios. Motivated by this, I examine the predictability of both the equity premium and its components. It might be that cash flow news and discount rate news are individually predictable because they are driven by different economic forces. They might lose their predictive power, however, when the components of the equity premium are intertwined with one another.

I use the return decomposition portfolios described above to study the predictability of the equity premium. Using portfolios allows for a clean separation of cash flow news from discount rate news. The returns of portfolios that consist of stocks that are driven mostly by cash flow news (discount rate news) might be predictable by variables that are related to future cash flows (future discount rate changes). There might also be variables that have predictive power, but that are not specifically related to one of these two components. As a result, no specific pattern across the return decomposition portfolios might be identifiable.

I use the predictive variables from Goyal and Welch (2008).[11] Due to the short sample period for the return decomposition (from July 1989 to December 2015, at

[11] I thank Amit Goyal for making the data available at: www.hec.unil.ch/agoyal/docs/PredictorData2015.xlsx.

best), I only consider monthly data and estimate in-sample predictive regressions. I do not estimate out-of-sample predictive regressions because this would result in an even shorter evaluation period. I first estimate the model on continuously compounded S&P 500 Index log returns (including dividends) and then estimate the models on the five portfolios individually.

From July 1989 to December 2015, the following four variables perform the best in predicting the (aggregate) equity premium: (i) stock variance, (ii) net equity expansion, (iii) dividend yield, and (iv) the dividend-price ratio. I present the results of three variables in Table 4.11. I omit the results for the dividend-price ratio because they are qualitatively similar to the dividend yield results. I do not present results on the other predictive variables as they yield mostly insignificant results both at the aggregate and portfolio level.[12] The table shows results for investment horizons ranging from one quarter to 28 quarters. The start date of the data examined is July 1989 for the shortest investment horizons (one, two, and four quarters). The start date of the data shifts with investment horizon up to July 1996, which corresponds to an investment horizon of 28 quarters. The end date of the data, which is common across investment horizons, is December 2015.

Although stock variance, net equity expansion, and the dividend yield have statistically significant predictive power, the forecast errors are large. At the aggregate level, the adjusted R^2s are positive but small. They are largest for stock variance (from 1.68 to 2.15). Net equity expansion and dividend yield have larger forecast errors (the adjusted R^2s range from 0.48 to 1.38 and from 0.67 to 1.96, respectively). The result that the forecast errors are so large is in line with the results in Goyal and Welch (2008).

Stock variance has significant predictive power at the aggregate level (the t-statistics range from −2.61 to −2.33). Its predictive power comes mostly from the extreme portfolios driven by discount rate news (the t-statistics range from −3.26 to −1.83). Stock variance also has predictive power on the intermediate portfolios,

[12] The other predictive variables I tried are: book-to-market ratio, default return spread, default yield spread, dividend-payout ratio, earnings-price ratio, inflation, long-term yield, long-term return, term spread, and Treasury bill rate. Fitting an AR1 model also yields insignificant results.

Table 4.11. Predictive Regressions at Monthly Frequency

This table presents statistics on in-sample equity premium forecasts using monthly data. The equity premium is that of the market (in logs), and of five portfolios sorted on the fraction of capital gain return variation that is driven by cash flow news. The predictor variables are: stock variance, net equity expansion, and dividend yield. The table reports results for investment horizons ranging from one quarter to 28 quarters. The sample starts at the indicated date, and ends in December 2015. The table shows adjusted R^2s and t-statistics of univariate predictive regressions. *, **, and *** indicate statistical significance levels of 10%, 5%, and 1%, respectively.

			Adjusted R^2						t-statistic					
Predictor	Hor	Start Sample	DR	2	3	4	CF	Mkt	DR	2	3	4	CF	Mkt
Stock Variance	1	1989:07	1.43	1.06	1.04	1.06	0.59	1.68	−2.37**	−2.09**	−2.08**	−2.09**	−1.69*	−2.53**
	2	1990:07	3.06	1.10	0.85	0.72	0.58	1.78	−3.26***	−2.09**	−1.90*	−1.79*	−1.67*	−2.56**
	4	1990:07	1.65	1.27	1.33	0.72	0.47	1.78	−2.47**	−2.22**	−2.26**	−1.79*	−1.57	−2.56**
	8	1991:07	0.80	2.28	1.50	0.71	0.68	1.94	−1.83*	−2.80***	−2.34**	−1.76*	−1.73*	−2.61***
	12	1992:07	2.53	1.51	1.30	0.70	0.95	2.02	−2.88***	−2.31**	−2.17**	−1.73*	−1.92*	−2.61***
	16	1993:07	1.34	2.19	1.07	0.90	0.67	2.01	−2.16**	−2.65***	−1.98**	−1.85*	−1.68*	−2.55**
	20	1994:07	1.87	1.52	1.49	1.35	0.70	2.15	−2.43**	−2.23**	−2.21**	−2.13**	−1.68*	−2.58**
	24	1995:07	1.39	1.14	2.63	1.29	0.49	2.02	−2.11**	−1.96*	−2.76***	−2.05**	−1.48	−2.46**
	28	1996:07	1.13	1.61	2.18	0.99	0.42	1.87	−1.92*	−2.19**	−2.49**	−1.82*	−1.41	−2.33**
Net Equity Exp.	1	1989:07	−0.02	0.38	0.06	0.19	0.54	0.48	0.97	1.48	1.09	1.26	1.65*	1.59
	2	1990:07	0.48	0.33	0.17	0.22	0.53	0.63	1.57	1.41	1.23	1.30	1.62	1.71*
	4	1990:07	0.13	0.21	0.30	0.32	0.51	0.63	1.18	1.28	1.39	1.40	1.60	1.71*
	8	1991:07	−0.02	0.51	0.17	0.32	0.66	0.70	0.97	1.58	1.23	1.39	1.72*	1.75*
	12	1992:07	0.67	0.46	−0.09	0.33	0.77	0.77	1.70*	1.52	0.86	1.39	1.78*	1.78*
	16	1993:07	−0.13	0.23	0.68	0.32	0.99	0.78	0.80	1.28	1.69*	1.36	1.92*	1.77*
	20	1994:07	0.35	0.57	0.69	1.37	1.75	1.38	1.38	1.57	1.67*	2.14**	2.36**	2.14**
	24	1995:07	0.66	0.56	0.64	0.93	1.63	1.30	1.62	1.54	1.61	1.82*	2.25**	2.05**
	28	1996:07	0.63	0.33	1.02	0.22	1.61	1.17	1.57	1.33	1.85*	1.23	2.19**	1.94*
Dividend Yield	1	1989:07	0.33	0.46	0.86	0.17	0.17	0.67	1.44	1.57	1.93*	1.24	1.24	1.77*
	2	1990:07	0.68	0.27	0.67	1.06	−0.20	0.76	1.76*	1.35	1.74*	2.06**	0.63	1.83*
	4	1990:07	0.34	0.78	0.43	0.77	−0.02	0.76	1.43	1.84*	1.52	1.84*	0.98	1.83*
	8	1991:07	0.58	0.54	1.31	1.02	−0.22	1.08	1.65	1.61	2.21**	2.01**	0.60	2.05**
	12	1992:07	1.00	0.73	1.60	1.79	0.12	1.27	1.96*	1.75*	2.36**	2.48**	1.16	2.15**
	16	1993:07	1.14	0.53	1.63	1.33	0.24	1.35	2.03**	1.56	2.33**	2.15**	1.28	2.17**
	20	1994:07	1.49	1.43	2.01	1.30	0.14	1.96	2.21**	2.17**	2.50**	2.09**	1.17	2.48**
	24	1995:07	1.61	0.71	2.11	1.74	0.73	1.76	2.24**	1.66*	2.51**	2.31**	1.67*	2.32**
	28	1996:07	1.66	0.62	0.88	2.90	0.28	1.50	2.22**	1.56	1.75*	2.82***	1.29	2.13**

although the significance levels are generally lower than those for the extreme discount rate news-driven portfolios (the t-statistics range from −2.80 to −1.73). The signs on the coefficients are negative across all portfolios and investment horizons, suggesting that increases in stock variance are predictive of lower future returns. It is intuitive that stock variance is most strongly predictive of returns for portfolios driven predominantly by discount rate news. When equity variance increases, investors become more risk averse and increase their discount rates, which leads to a decrease in returns. This effect is stronger the more returns are driven by discount rate news.

Unlike stock variance, net equity expansion has weak predictive power at the aggregate level (the t-statistics range from 1.59 to 2.14). Nevertheless, any predictability comes mostly from the extreme portfolios that include stocks with returns that are mostly driven by cash flow news. The signs are positive, which indicates that future returns increase with equity issuance. It is intuitive that this variable is the most strongly predictive when the returns are driven predominantly by cash flow news. In general, firms issue equity to invest in positive NPV projects. As a result, investors increase their future cash flow forecasts such that stock returns increase.

The predictive power of the dividend yield at the aggregate level is generally significant (the t-statistics range from 1.77 to 2.48). Unlike the previous two variables, it is not immediately clear whether this predictability comes from cash flow news or discount rate news. This is because price is in the denominator, which is a function of both cash flow news and discount rate news. The results at the portfolio level in Table 4.11 do not show any systematic pattern as to whether it is driven by cash flow news or discount rate news.

Overall, the results suggest that the sources of stock price variation play an important role in the predictability of the equity premium. I find that the predictive power of stock variance is predominantly driven by the cash flow news-driven stocks, that the predictive power of net equity issuance is predominantly driven by the discount rate news-driven stocks, and that the predictive power of the dividend yield and dividend-price ratio originates from both components. Nevertheless, the forecast errors are large for all four variables both at the portfolio and aggregate level.

4.5 Co-Movement in Stock Returns

As an explanation for the co-movement in stock returns, researchers have examined the role of, among others, information availability, the strength of public investor property rights (Morck, Yeung, and Yu, 2000), and the strength of the institutional environment (Dang, Moshirian, and Zhang, 2015). In this section, I explore the role of the sources of stock price variation. If stock return co-movement is driven by common exposures to economic shocks, it must be traced back to the sources of stock price variation. On the one hand, a systematic shock to cash flows might induce co-movement in the stock returns that are predominantly driven by cash flow news. On the other hand, a systematic shock to discount rates might induce co-movement in the stock returns that are predominantly driven by discount rate news (Campbell, Polk, and Vuolteenaho, 2010). Given the conclusion in the literature that cash flow news is diversified away more than discount rate news (Chen, Da, and Zhao, 2013, and the references therein), I would expect to find relatively more co-movement in discount rate news (so that it is more difficult to diversify discount rate news away). Understanding co-movement in the drivers of stock price variation is important because it affects the ease of diversification of the components of stock price variation.

Following Morck, Yeung, and Yu (2000), I use R^2 as a measure of co-movement in stock returns. For each portfolio and each horizon, I estimate full-sample univariate regressions of the returns of the stocks in that portfolio on five return decomposition portfolios. In particular, I use the R^2 from the following regression:

$$R_{i,p,t} = \alpha_{i,p} + \beta_{i,p} R_{p,t} + \varepsilon_{i,p,t}, \tag{4.1}$$

where $R_{i,p,t}$ is the return of stock i in portfolio p at month t and $R_{p,t}$ is the value-weighted return of portfolio p at time t (excluding stock i when the stock is included in the portfolio). In this univariate framework, the R^2 is equal to the squared Pearson correlation coefficient. Next, I take the cross-sectional average of the R^2 for each group of stocks and estimate bootstrap-based confidence intervals.

Table 4.12. Stock Return Co-Movement

Stocks are sorted into five portfolios as of the end of June of each year based on the fraction of capital gain return variation that is driven by cash flow news. For investment horizons ranging from one quarter to 28 quarters, the table reports the average $\boldsymbol{R}^2$ of regressions of the returns of stock $\boldsymbol{i}$ on portfolio returns (excluding stock $\boldsymbol{i}$, if applicable). The bootstrap-based 95% non-parametric confidence intervals are in brackets. The table reports results for the first (DR), third (CF&DR), and fifth (CF) quantiles of firms and portfolios. The start date ranges from July 1989 (one quarter investment horizon) to July 1996 (28 quarters investment horizon) and the end date is December 2015.

	DR portfolio	CF&DR portfolio	CF portfolio	DR portfolio	CF&DR portfolio	CF portfolio
	1 quarter			16 quarters		
DR firms	14.7	15.0	15.3	16.8	16.2	15.5
	[14.1, 15.4]	[14.3, 15.7]	[14.6, 15.9]	[16.1, 17.6]	[15.4, 17.0]	[14.7, 16.3]
CF&DR firms	15.4	15.6	15.5	18.1	17.6	16.7
	[14.8, 16.0]	[15.0, 16.2]	[14.9, 16.1]	[17.3, 18.8]	[16.8, 18.3]	[15.9, 17.5]
CF firms	14.3	14.0	15.3	16.9	16.1	18.2
	[13.7, 15.0]	[13.3, 14.6]	[14.6, 16.0]	[16.0, 17.6]	[15.4, 16.9]	[17.3, 19.0]
	2 quarters			20 quarters		
DR firms	16.1	15.5	13.9	16.6	16.3	15.1
	[15.4, 16.8]	[14.8, 16.2]	[13.3, 14.6]	[15.7, 17.4]	[15.4, 17.1]	[14.3, 15.9]
CF&DR firms	16.9	16.3	14.0	18.1	18.9	16.6
	[16.3, 17.6]	[15.7, 17.0]	[13.4, 14.6]	[17.4, 18.9]	[18.0, 19.7]	[15.9, 17.3]
CF firms	15.2	14.4	14.8	17.1	16.6	17.1
	[14.6, 15.9]	[13.8, 15.0]	[14.2, 15.4]	[16.3, 17.9]	[15.9, 17.4]	[16.3, 17.8]
	4 quarters			24 quarters		
DR firms	16.6	15.8	14.4	17.4	16.3	15.6
	[15.8, 17.3]	[15.1, 16.5]	[13.8, 15.1]	[16.5, 18.2]	[15.4, 17.1]	[14.7, 16.3]
CF&DR firms	16.1	15.7	14.5	19.0	17.7	16.6
	[15.4, 16.8]	[15.0, 16.4]	[13.9, 15.1]	[18.2, 19.8]	[16.9, 18.5]	[15.9, 17.3]
CF firms	15.3	14.9	15.6	17.3	16.0	16.3
	[14.6, 16.0]	[14.2, 15.6]	[14.9, 16.2]	[16.5, 18.1]	[15.2, 16.8]	[15.5, 17.1]
	8 quarters			28 quarters		
DR firms	16.2	16.1	15.0	17.2	16.2	15.4
	[15.4, 16.9]	[15.3, 16.8]	[14.2, 15.7]	[16.3, 18.1]	[15.3, 17.2]	[14.5, 16.2]
CF&DR firms	16.8	17.0	16.0	19.0	18.2	15.9
	[16.1, 17.5]	[16.3, 17.6]	[15.4, 16.7]	[18.2, 19.8]	[17.4, 19.0]	[15.1, 16.6]
CF firms	15.5	15.4	17.1	17.4	15.6	15.7
	[14.7, 16.2]	[14.7, 16.1]	[16.3, 17.9]	[16.6, 18.2]	[14.8, 16.4]	[14.9, 16.6]
	12 quarters					
DR firms	16.2	16.2	15.0			
	[15.4, 17.0]	[15.4, 17.0]	[14.3, 15.8]			
CF&DR firms	17.5	17.5	16.4			
	[16.8, 18.2]	[16.7, 18.2]	[15.7, 17.1]			
CF firms	16.1	15.8	17.9			
	[15.3, 16.9]	[15.1, 16.6]	[17.1, 18.7]			

The results in Table 4.12 show that stocks driven by discount rate news exhibit more return co-movement than stocks driven by cash flow news, although the economic magnitudes are small. At investment horizons of two quarters and longer, the R^2s from regressions of discount rate news-driven stock returns on discount rate news-driven portfolio returns are significantly higher than when they are regressed on cash flow news-driven portfolio returns. At the 28-quarter horizon, for example, the average R^2 of discount rate news-driven stocks with regard to the discount rate news-driven portfolio is 17.2%, while the R^2 with regard to the cash flow news-driven portfolio is lower at 15.4%. This difference is small but statistically significant. Stocks driven by cash flow news have R^2s with respect to the different portfolios that are not statistically different, suggesting that they do not exhibit more co-movement with similarly classified stocks. The finding that discount rate news-driven stocks have relatively more co-movement suggests that discount rate news is more difficult to diversify away than cash flow news. This is in line with Chen, Da, and Zhao (2013), who find that cash flow news is diversified away more than discount rate news at the market level.

4.6 Conclusion

An important question in asset pricing is to what extent cash flow news and discount rate news drive stock price variation. This paper examines the cross-sectional variation in the importance of cash flow news and discount rate news. The results show that firms differ greatly in the extent to which these two components drive stock price variation. This is important, because if discount rates are stationary, then the prices of discount rate news-driven stocks should be stationary too. Long-term investors should therefore be primarily concerned with cash flow news. In line with this hypothesis, I find that cash flow news-driven stocks offer higher returns than discount rate news-driven stocks. The corresponding premium is economically large and generally statistically significant, especially when it is corrected for exposure to multiple risk factors.

I also examine two important practical applications of the return decomposition. The first application concerns the predictability of the equity premium. Since the equity premium, just like stock returns, is driven by cash flow news and discount rate news, its predictability is likely to be driven by two economic channels. My results suggest that the predictive variables might be successful because they predict the returns of stocks driven by cash flow news, discount rate news, or both. Given the instability of predictive models (Goyal and Welch, 2008), a slight improvement in the predictive power of the models by considering the return components is valuable. The second application concerns stock returns co-movement. I show that discount rate news-driven stocks exhibit higher return co-movement than cash flow news-driven stocks. Although the economic magnitude is small, this finding has important implications for investors. In particular, it suggests that discount rate risk is more driven by common fundamental factors than cash flow risk such that investing in discount rate news-driven stocks is relatively risky. However, this might be a concern only for short-term investors and not for long-term investors when discount rates are stationary.

Appendices

4.A Estimating the Implied Cost of Capital

In this appendix, I explain how I estimate the implied cost of capital (ICC). I back out the ICC from an empirically tractable finite-horizon present value model in which the current stock price equals the discounted expected future dividends:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k}(1-b_{t+k})}{(1+q_t)^k} + \frac{FE_{t+T+1}}{q_t(1+q_t)^T}, \tag{4.A.1}$$

where P_t is the stock price, FE_{t+k} is the conditional expectation of k-year ahead earnings, b_{t+k} is the expected plowback rate ($1-b_{t+k}$ is the net payout ratio), and q_t is the ICC. The first part on the right-hand side discounts future cash flows from year $t+1$ to year T. The second term is a discounted no-growth perpetuity that captures cash flows beyond terminal year T in which earnings growth and the plowback rate are assumed to reach their steady states. The assumption underlying the terminal value perpetuity is that no economic profits are earned after year T. I set T equal to 15. In each month, I trim outliers by deleting the top and bottom 0.5% of the ICC distribution.

Expected free cash flows

I obtain one-, two-, and three-years ahead earnings forecasts, long-term earnings growth forecasts, share prices, and numbers of shares outstanding from IBES. The sample period starts in 1985 due to limited data availability before that period. I use forecasts as of the end of every quarter (March, June, September, and December) and require stock prices to be at least $1.

To be included in the analysis, I require the long-term earnings growth rate to be available, and at least one of the following two data items to be available: the one-year ahead earnings forecast and/or the two-years ahead earnings forecast. To ensure reasonable and bounded forecasts of future earnings, I winsorize earnings growth rates above 100% (below 2%) to 100% (2%). If the one- or two-years ahead earnings forecast is unavailable, I estimate it via the relation $FE_{t+2} = FE_{t+1} \times (1+g_2)$.

I require the earnings forecasts at both $t+1$ and $t+2$ to be positive. I use the earnings growth rate and the two-years ahead earnings forecast to estimate three-year ahead expected earnings as $FE_{t+3} = FE_{t+2} \times (1+g_2)$ if the three-years ahead earnings forecast is unavailable.

To estimate the expected earnings for years $t+4$ through $t+T+1$, I assume that the expected earnings growth rate converges exponentially to the industry growth rate g^{ind}:

$$g_{t+k} = g_{t+k-1} \times e^{log(\frac{g^{ind}}{g_{t+3}})/(T-1)}. \tag{4.A.2}$$

I base the industry classification on two-digit SIC codes. I use the growth rates to obtain expected future earnings forecasts for years $t+4$ through $t+T+1$ as follows:

$$FE_{t+k} = FE_{t+k-1} \times (1 + g_{t+k}). \tag{4.A.3}$$

From year $t+T+2$, I assume that earnings are equal to the long-term GDP growth rate. I retrieve GDP growth data from the Bureau of Economic Analysis.[13] The starting date of the data is 1930, and the long-term GDP growth rate is estimated based on the data available at the time of estimation.

Expected plowback rates

For years $t+1$ and $t+2$, I assume that the plowback rate is equal to the current net payout ratio. I use accounting data from Compustat to estimate the plowback rates. I estimate the plowback rate by dividing current dividends (DVC) by net income (IBCOM). If net income is negative, I set it to 6% of total assets (AT). I winsorize net payout ratios above 100% (below 0%) to 100% (0%).

After the first two years, I assume that the plowback rate converges to a steady state by year $t+T+2$. In particular, I assume that the steady-state earnings growth rate equals the return on new investment (ROI) times the plowback rate. In addition, I assume that, in the steady state, ROI converges to the cost of capital, which means

[13] www.bea.gov/national/xls/gdplev.xls.

that earnings accurately reflect risks in the long run. I also assume that earnings growth converges to the market growth rate. Thus, the steady-state plowback rate is estimated as $b = g/q$. I restrict the plowback rate to be at most 95%. In years $t+3$ through $t+T+1$, I assume that plowback rates converge linearly to the steady state:

$$b_{t+k} = b_{t+k} - \frac{b_{t+2} - b}{T-1}. \tag{4.A.4}$$

4.B Discount Rate News and Cash Flow News

I follow Chen, Da, and Zhao (2013) to decompose a capital gain return into a cash flow news component and discount rate news component via:

$$Retx_t(k) = \frac{P_t - P_{t-k}}{P_{t-k}} = \frac{f(c_t, q_t) - f(c_{t-k}, q_{t-k})}{f(c_{t-k}, q_{t-k})} = Retx_j^{CF}(k) + Retx_j^{DR}(k) \quad (4.B.1)$$

where:

$$Retx_t^{CF}(k) = \frac{f(c_t, q_t) - f(c_{t-k}, q_t)}{2f(c_{t-k}, q_{t-k})} + \frac{f(c_t, q_{t-k}) - f(c_{t-k}, q_{t-k})}{2f(c_{t-k}, q_{t-k})} \quad (4.B.2)$$

and

$$Retx_t^{DR}(k) = \frac{f(c_{t-k}, q_t) - f(c_{t-k}, q_{t-k})}{2f(c_{t-k}, q_{t-k})} + \frac{f(c_t, q_t) - f(c_t, q_{t-k})}{2f(c_{t-k}, q_{t-k})}. \quad (4.B.3)$$

These equations reflect that stock prices are a function of expected cash flows (c_t) and discount rates (q_t): $P_t = f(c_t, q_t)$. $Retx_t^{CF}(k)$ reflects the price change that is driven by changing expectations about future cash flows over k quarters and keeping discount rates constant. $Retx_t^{DR}(k)$ reflects the price change that is driven by changes in discount rates over k quarters and keeping expectations about future cash flows constant. These hypothetical prices are estimated twice: once assuming that the discount rates (when estimating $Retx_t^{CF}(k)$) or cash flows (when estimating $Retx_t^{DR}(k)$) in both periods are equal to past expectations, and once assuming that they are equal to current expectations. Next, an average of the two price changes is taken. To see how this decomposition is related to the Campbell and Shiller (1988) decomposition, see Chen, Da, and Zhao (2013).

Next, I estimate the fraction of the stock price variance driven by cash flow news and discount rate news by regressing, respectively, $Retx^{CF}$ and $Retx^{DR}$ on $Retx$. The fraction of capital gain return variance driven by the two news components is then:

$$\frac{cov(Retx_t^{CF}, Retx_t)}{var(Retx_t)} + \frac{cov(Retx_t^{DR}, Retx_t)}{var(Retx_t)} = CF + DR = 1. \quad (4.B.4)$$

CF and DR represent the fractions of capital gain return variation that is driven by cash flow news and discount rate news, respectively.

4.C Construction of Firm Characteristic Variables

In this appendix, I provide details on the construction of the firm characteristics. The construction of the variables that capture size, book-to-market ratio, profitability, and investments closely follows Fama and French (2015). I obtain accounting data from Compustat and data on stock returns from CRSP.

I define the book value of equity as stockholders' equity (SEQ) plus deferred taxes and investment tax credit (TXDITC), if available, minus the redemption value of preferred stock (PSTKRV). If stockholders' equity is unavailable, I construct it by subtracting total liabilities (LT) from total assets (AT). If the redemption value of preferred stock is unavailable, I use the liquidating value of preferred stock (PSTKL) or the book value of preferred stock (PSTK), in that order. The book-to-market ratio is defined as the book value of equity at the end of fiscal year $t-1$ divided by the total market value of equity at the end of December of year $t-1$. The market value of equity is computed from CRSP data and defined as the number of shares outstanding (SHROUT) times the closing price (PRC).

I define profitability as revenues (REVT) minus costs of goods sold (COGS), minus selling, general, and administrative expenses (XSGA), and minus interest and related expenses (XINT), all divided by the stockholders' equity (SEQ). If stockholders' equity is unavailable, I construct it as described above. I define investment as the growth in total assets. I take the natural logarithm of total assets (AT) at the end of fiscal year $t-2$ divided by total assets at the end of fiscal year $t-1$. The dividend dummy takes a value of 1 when dividends (DVC) are positive. Leverage is defined as long-term debt (DLTT) plus debt in current liabilities (DLC), all divided by stockholders' equity (SEQ). All these variables are taken as of the end of fiscal year $t-1$. I winsorize all variables at the 1% level before calculating the characteristics of the return decomposition portfolios.

4.D Cash Flow and Discount Rate Betas

I follow Campbell (1991) and Campbell and Vuolteenaho (2004) and use the VAR methodology to estimate cash flow news and discount rate news. I include the excess market return, yield spread, price-earnings ratio, and small stock value spread in the state vector. I define excess market return as the log value-weighted return on the CRSP market index minus the log risk-free rate. I measure the term yield spread as the long-term yield (from Goyal and Welch, 2008) minus the risk-free rate. I retrieve the data to construct the price-earnings ratio from Shiller's website.[14] The price-earnings ratio is defined as the log ratio of the S&P 500 prices over a ten-year moving average of aggregate S&P 500 earnings. The small stock value spread is the log book-to-market ratio of small value stocks minus that of small growth stocks. I construct the small stock value spread as of the end of June at year t, using the book and market equity measured at year $t-1$. For the remaining months following June, I add the difference between the cumulative log return of the small low book-to-market portfolio and the small high book-to-market portfolio to the small stock value spread estimated for June. The estimation period is from December 1928 until December 2015.

Next, I estimate the cash flow beta as:

$$\beta_{i,CF} = \frac{cov(R_{i,t}, N_{CF,t})}{var(R_{M,t} - E_{t-1}(R_{M,t}))} \tag{4.D.1}$$

and the discount rate beta as:

$$\beta_{i,DR} = \frac{cov(R_{i,t}, -N_{DR,t})}{var(R_{M,t} - E_{t-1}(R_{M,t}))}, \tag{4.D.2}$$

where $N_{CF,t}$ and $N_{DR,t}$ are the market cash flow and discount rate news components, respectively, generated by the VAR model. The numerator in the discount rate beta equation is the covariance of stock returns with the negative of the market discount rate news component. As a result, the covariance is positive when returns increase

[14] I thank Robert Shiller for making the data available. The data are found at: http://www.econ.yale.edu/ shiller/data/ie_data.xls.

due to decreases in discount rates, just like when returns increase after a positive cash flow shock occurs. The denominator in both betas is the variance of unexpected market returns, such that the betas sum to the CAPM market beta:

$$\beta_{i,CAPM} = \beta_{i,CF} + \beta_{i,DR}. \tag{4.D.3}$$

Chapter 5

Summary and Concluding Remarks

This dissertation consists of three papers on empirical asset pricing. In the broadest possible sense, in each of the three papers I investigate why asset prices vary over time and in the cross-section, and how this information can be used by investors and managers to make investment and corporate finance decisions.

In Chapter 2, I investigate whether common risk factors are priced across investment horizons. I decompose stock returns and risk factors into components associated with different horizons and estimate separate risk loadings at each horizon. I proceed by including the horizon-specific risk loadings in Fama and MacBeth (1973) cross-sectional regressions to determine the risk premia associated with the different factors at each horizon. I show that only the market and size factors are priced, but only up to sixteen months. Overall, the results of this chapter highlight the importance of horizon effects in the pricing of systematic risk, but also raise concerns about the ability of asset pricing models to price individual stocks.

In Chapter 3, I estimate costs of equity capital for individual firms and industries using five models: (1) the CAPM, (2) the Fama and French (1993) three-factor model, (3) the Carhart (1997) four-factor model, (4) the Fama and French (2015) five-factor model, and (5) the Hou, Xue, and Zhang (2015) four-factor model. I examine (i) model disagreement, (ii) estimation uncertainty, and (iii) forecasting power for future returns. I find that the models differ greatly in their expected return point estimates, but that the standard errors around these point estimates are so large that these differences are often not statistically significant. All the models exhibit some forecasting power for future returns, but only when the standard errors are small. My results raise questions about the applicability of popular asset pricing models for computing costs of equity capital. They further indicate a trade-off between the improved in-sample pricing ability of models with more factors and the increased expected return standard errors that such models yield.

In Chapter 4, I examine the sources of stock price variation and show that firms differ greatly in the extent to which their stock prices are driven by cash flow news versus discount rate news. The differences in the relative importance of the drivers of stock price variation are associated with differences in firm characteristics, risk exposures, and expected returns. I also show that the sources of stock price variation are important because the amount of stock return co-movement and the success of variables that predict the equity premium depend on the extent to which stocks are driven by cash flow news versus discount rate news.

Nederlandse Samenvatting (Summary in Dutch)

Dit proefschrift bestaat uit drie artikelen over het empirisch prijzen van financiële producten. In de breedst mogelijke zin onderzoek ik in elk van de drie hoofdstukken waarom activaprijzen over de tijd en in de doorsnede variëren en hoe deze informatie door beleggers en managers kan worden gebruikt om beleggings- en bedrijfsfinanciële beslissingen te nemen.

In hoofdstuk 2 onderzoek ik of gebruikelijke risicofactoren over verschillende beleggingshorizons zijn geprijsd. Ik ontleed de aandelenrendementen en risicofactoren in componenten die gekoppeld zijn aan verschillende horizons en schat afzonderlijke risicoblootstellingen op elke horizon. Vervolgens voeg ik de horizon-specifieke risicoblootstellingen toe in Fama and MacBeth (1973) dwarsdoorsnede-regressies om de risicopremies van de verschillende factoren te bepalen per horizon. Ik laat zien dat alleen de markt- en *size*-factor geprijsd zijn, maar slechts tot een horizon van zestien maanden. Over het geheel genomen laten de resultaten van dit hoofdstuk zien dat horizon-effecten belangrijk zijn bij de prijsbepaling van systematisch risico, maar ze geven ook aanleiding tot bezorgdheid over het vermogen van activaprijsmodellen om individuele aandelen te prijzen.

In hoofdstuk 3 schat ik de vermogenskostenvoet voor individuele bedrijven en industrieën aan de hand van vijf modellen: (1) het CAPM, (2) het Fama and French (1993) drie-factor model, (3) het Carhart (1997) vier-factor model, (4) het Fama and French (2015) vijf-factor model, en (5) het Hou, Xue, and Zhang (2015) vier-factor model. Ik onderzoek (i) verdeeldheid tussen modellen, (ii) schattingsonzekerheden, en (iii) voorspellingskracht voor toekomstige rendementen. Ik laat zien dat de modellen sterk verschillen in hun punt schattingen van het verwachte rendement, maar dat de standaard fouten rondom deze punt schattingen zo groot zijn dat deze verschillen vaak niet statistisch significant zijn. Alle modellen hebben voorspellende vermogens voor toekomstige rendementen, maar alleen als de standaardfouten klein zijn. Mijn resultaten roepen vragen op over de toepasbaarheid van populaire activaprijsmodellen voor het berekenen van de vermogenskostenvoet. Zij wijzen verder op een afweging tussen het verbeterde in-sample vermogen om prijsvariatie te verklaren van modellen met meer factoren en de verhoogde standaardfouten van de verwachte rendementen die dergelijke modellen voorbrengen.

In hoofdstuk 4 onderzoek ik de bronnen van variatie in aandelenkoersen en laat zien dat bedrijven sterk verschillen in de mate waarin hun aandelenkoersen worden aangedreven door nieuws over kasstromen en de verdisconteringsvoet. De verschillen in het relatieve gewicht van de aandrijvers van variatie in aandelenkoersen worden geassocieerd met verschillen in bedrijfskarakteristieken, risicoblootstellingen en verwachte rendementen. Ik laat ook zien dat de bronnen van de koersveranderingen belangrijk zijn omdat de mate van gemeenschappelijkheid in koersbewegingen en het succes van variabelen die de marktpremie voorspellen afhangen van de mate waarin aandelen worden gedreven door nieuws over kasstromen versus de verdisconteringsvoet.

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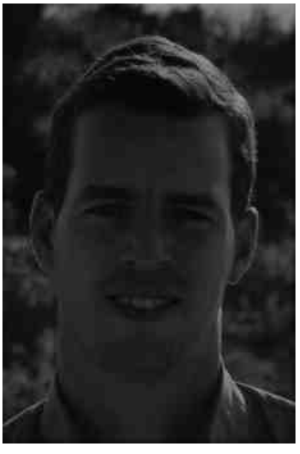
About the Author



Roy Verbeek was born on February 23, 1990 in Tiel, The Netherlands. He received his BSc degree in International Business Administration (*cum laude*) in 2011, his MSc degree in Finance and Investments (*cum laude*) in 2012, and his MPhil degree in Business Research with a specialisation in Finance (*cum laude*) in 2013. All degrees are from Rotterdam School of Management, Erasmus University.

In September 2013, Roy joined the Department of Finance at Rotterdam School of Management as a PhD candidate. His PhD research was supported by a Research Talent grant from The Netherlands Organisation for Scientific Research (NWO) and supervised by Mathijs van Dijk and Marta Szymanowska. In the fall of 2016, he spent three months at BI Norwegian Business School in Oslo, Norway, as a visiting PhD candidate. Roy taught workshops for the BSc course Corporate Finance and supervised BSc and MSc theses.

Starting from September 2017, Roy will be working as an Assistant Professor of Finance at Nyenrode Business University in Breukelen, The Netherlands.

Portfolio

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	MSc in Finance and Investments *cum laude* Rotterdam School of Management, Erasmus University	2011 - 2012
	BSc in International Business Administration *cum laude* Rotterdam School of Management, Erasmus University Exchange visit to Manchester Business School, University of Manchester	2008 - 2011
Working Papers	**The Pricing of Systematic Risk Factors across Horizons** with Marta Szymanowska and Mathijs van Dijk	
	Using Factor Models to Compute Costs of Equity Capital single-authored, job market paper	
	Understanding the Sources of Stock Price Variation single-authored	
Conferences & seminars	Brownbag Seminar, BI Norwegian Business School PhD Workshop, 33rd International Conference of the French Finance Association PhD Seminar, Rotterdam school of Management, Erasmus University	2016
	PhD Seminar, Rotterdam school of Management, Erasmus University	2015
Honours & Awards	Research Talent Grant from Netherlands Organisation for Scientific Research (NWO)	2013
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Propositions attached to the thesis

Essays in Empirical Asset Pricing

by Roy Verbeek

Rotterdam School of Management

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I

Prices of risk vary with investment horizon. (Chapter 2)

II

Estimates of the cost of equity capital are very sensitive to the choice of asset pricing model. (Chapter 3)

III

When the cost of equity capital is relatively imprecisely estimated, its use in capital budgeting and valuation is limited because it is not informative about future returns. (Chapter 3)

IV

Including more risk factors that are priced in-sample into an asset pricing model does not necessarily lead to better out-of-sample stock return forecasts. (Chapter 3)

V

Firms differ greatly in the extent to which their stock prices are driven by cash flow news and discount rate news. (Chapter 4)

VI

Although many asset pricing models are able to explain portfolio returns, they usually have great difficulty in pricing individual stocks.

VII

Investors and financial managers should evaluate the cash flow and discount rate news components of stock price variation separately for making investment and corporate financing decisions.

VIII

Producing good empirical finance research is hard, if not impossible, without great programming skills.

IX

Replication studies are highly undervalued.

X

To succeed as an academic one needs to have intellect, luck, and selling skills.

XI

Great research questions are hard to find, while great results are hard to believe.

This dissertation consists of three essays on empirical asset pricing. In the first essay, I investigate whether common risk factors are priced across investment horizons. I show that only the market and size factors are priced, but only up to sixteen months. The results highlight the importance of horizon effects in the pricing of systematic risk. They also raise concerns about the ability of asset pricing models to price individual stocks. In the second essay, I estimate costs of equity capital for individual firms and industries using five models. I show that there is considerable disagreement about costs of equity capital across the models and that they are estimated with great errors. The models exhibit some forecasting power for future returns only when the estimation errors are small. My results raise questions about whether popular asset pricing models can be used for computing costs of equity capital. In the third essay, I show that firms differ greatly in the extent to which their stock prices are driven by cash flow news versus discount rate news. The differences in their relative importance are associated with differences in firm characteristics, risk exposures, and expected returns. I also show that the amount of return co-movement and the success of variables that predict the equity premium depend on the relative importance of the two components.

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