Real options and the term structure of equity

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Abstract

Short-term real options are more sensitive to aggregate shocks than long-term real options because they are closer to being exercised and converted to assets-in-place, and thus have a larger real option delta. Consequently, equities with embedded short-term real options are riskier and earn higher returns on average than do equities with embedded long-term real options. This mechanism is stronger the more real options are embedded, for example, for growth firms. I show empirically that the average returns of short duration growth stocks with embedded short-term real options are significantly higher than the average returns of long-duration growth stocks with embedded long-term real options, that is, the term structure of returns for growth stocks is downward sloping. Moreover, systematic risk, as measured by cash-flow betas, also exhibits a downward sloping term structure for growth firms. In contrast, both long- and short-duration value stocks possess little real options, and hence their return (and cash-flow beta) difference is not significantly different from zero; the term structure of returns for value stocks is flat. A two-factor model, with cash flow and discount rate, captures the cross-sectional variation of returns across stocks sorted by duration and the book-to-market ratio.

Keywords: Real options theory, Cross-section of stock returns, Term structure of equity

1 Introduction

The term structure of equity returns, that is, equity yields across different timing horizons, is downward sloping (van Binsbergen, Brandt, and Koijen, 2012), i.e. short-term equities earn, on average, higher returns than long-term equities do. This empirical finding is unexpected because leading asset pricing models such as Campbell and Cochrane (1999), Bansal and Yaron (2004), and Barro (2006) all imply an upward sloping or flat term structure of equity returns. Different classes of models are proposed to explain this new empirical fact. [1]

This article suggests that the real options theory can be an explanation. According to the real options theory, a firm's total value can be decomposed into two components, real options and assets-in-place. Short-term equities earn higher returns than do long-term equities, because short-term real options embedded in short-term equities are riskier than long-term real options embedded in long-term equities. The intuition comes from the concept of option charm (delta decay), one of the financial option greeks that indicates how much of the option delta, the sensitivity of the option value to the underlying asset, would change across different time-to-maturities. For an in-the-money financial option, the shorter is the time-to-maturity, the higher is the option delta, and, hence, the more volatile is the option. This occurs because options with shorter expiration that are deep in-the-money tend to behave like underlying stocks. Analogously, the riskiness of a real option is related to aggregate shocks through its sensitivity (option delta) to the variation of the underlying asset to which the real option is converted. Such sensitivity is greater for short-term real options than long-term real options, because short-term real options are soon to be exercised and converted into assets-in-place.

There are two main empirical implications of the real option theory. First, the theory says that the downward sloping term structures of equity returns is mainly driven by the risk exposure of real options. If the theory is true, firms with more real options should exhibit a steeper downward sloping pattern, e.g. growth firms. This implication is unique to the real options theory, and can help to distinguish between the real options theory and alternative explanations. For example,

[1] See van Binsbergen and Koijen (2017) for a review of different classes of models.

another strand of production-based models focus on the operating leverage channel. They argue that the downward sloping term structure of returns arises because firms' operating leverage, in the form of either physical capital or labor, is difficult to adjust in the short-run, so that firms are more vulnerable when faced with negative shocks (see Favilukis and Lin, 2016; Marfe, 2015). If this alternative explanation is true, then firms with more operating leverage should exhibit steeper downward sloping pattern, e.g. value firms, which however is inconsistent with my empirical finding.

Second, there is a debate in the literature about whether the term structure of equity returns is due to the variation of risk exposures or risk prices (van Binsbergen and Koijen, 2017). According to the real options theory, the source of variation comes from risk exposures. Consequently, stock returns across different time-to-maturity of cash flows should align with their corresponding betas with respect to aggregate shocks. This prediction contrasts with the implication of consumption-based models in the sense that these models only emphasize the variation of risk prices, and have no implications on the term structures of returns for cross sectional stocks (see Curatola, 2015; Eisenbach and Schmalz, 2016; Andries, Thomas Eisenbach, and Schmalz, 2017). In other words, if, to an extreme, only the risk prices matter according to these consumption models, then all the individual stocks should exhibit the same downward sloping term structure pattern. In this article, the aggregate shock is defined as the cash flow shock. This is inspired by Campbell and Vuolteenaho (2004), who show that the beta with respect to cash flow shock is greater for value stocks than for growth stocks. Their result is an indirect inference to the alignment between stock returns and risk exposures over the term structure, because growth stocks are usually considered long-term assets, while value stocks are considered short-term assets. [2]

My empirical analysis begins with the construction of the term structure of equity returns, which involves an identification of long- and short-term equity. For example, van Binsbergen, Brandt, and Koijen (2012) extract dividend strips of the market index from the options data. Such dividend strips are considered short-term equities, which are then compared with the market index,

[2] van Binsbergen et al. (2012) show that the short-term dividend claims have lower market beta than the market index. The market beta however may not be a proper measure for the aggregate shock in this study.

considered long-term equity. This approach however is not feasible in this study, because the liquidities of financial derivatives for most of the individual stocks are thin. Therefore, I choose to use the duration approach in the spirit of Weber (2016). I compute the firm specific cash-flow duration following Dechow et al. (2004), which resembles the traditional Macaulay duration for bonds and reflects the weighted average time to maturity of cash flows. The stock returns sorted by the cash-flow-duration inform about the term structure of equity yields. The advantage of this empirical method is that it can be easily applied in the cross sectional analysis. Specifically, I double-sort the sample on duration and some firm characteristics that proxy for real options, such as book-to-market ratio. The duration quintiles for the growth stocks represent the term structure of returns for stocks with more real options, while the duration quintiles for the value stocks represent the term structure of returns for stocks with more assets-in-place. I find that the average monthly return of short-duration growth stocks is 0.72%, significantly higher than that of long-duration growth stocks, while the return difference between short- and long-duration value stocks does not differ significantly. That is, the term structure of returns for growth stocks is downward sloping, while that for the value stocks is flat. Moreover, I also show that the term structure of cash-flow betas for the growth stocks is downward sloping, while term structure of cash flow betas for the value stocks is flat. These results are consistent with the two theoretical implications mentioned above.

To check whether the cash flow risk is realistically priced to explain the duration return spread, I conduct an asset pricing test with a two-factor model similar to Campbell and Vuolteenaho (2004). Using a two-stage regression, I show that the price of cash flow risk is 0.31% per month, significantly different from zero. Note that this asset-pricing test using a two-stage regression implicitly assumes that the prices of risks are constant, which means any variation of portfolio returns across duration is driven by only the betas. Under such restrictive assumption, the two-factor model can still predict a large fraction (68%) of the realized duration spread. This result supports the importance of the risk exposure channel, rather than risk price channel as debated by other studies, in driving the term structure of returns.

While a wide variety of theoretical mechanisms have been proposed to explain the term structure of equity returns (see van Binsbergen and Koijen, 2017, for a comprehensive review), this paper adds the real options theory to the list of explanations. Empirical research in this area however is relatively limited because of the lack of data. van Binsbergen, Brandt, and Koijen (2012) and van Binsbergen, Hueskes, Koijen, and Vrugt (2013) are empirical examples that study the term structure of returns for the market portfolio, which are subject to debates (Boguth, Carlson, Fisher, and Simutin, 2012; Schulz, 2016; van Binsbergen and Koijen, 2016; Cochrane, 2017). Other papers approach the term structure problem by drawing inference from the cross section (Da, 2009; Dechow, Sloan, and Soliman, 2004; Weber, 2016; Ai, Croce, Diercks, and Li, 2017). This paper approaches the problem using cross sectional data as well, but in contrast to Weber (2016) who study stock returns across only the duration dimension, I look at the returns across duration separately for different portfolios sorted by firm characteristics.

This paper is also related to the literature that relates real options and cross-sectional asset pricing (Cooper, 2006; Ai and Kiku, 2013; Hackbarth and Johnson, 2015). Real options allow more flexibility for firms to choose when and how to invest (or disinvest). Firms would choose to invest (or disinvest) only if the net present value (NPV) from doing so exceeds the option value of waiting. As a result, there exists a region of firm value within which the firms would not react to aggregate shocks, i.e. these firms have less aggregate risk sensitivity, and earn lower returns. One thing in common for these papers is that they emphasize the difference in terms of riskiness between real options and assets-in-place. In contrast, I emphasize the riskiness of real options and assets-in-place along the horizon of cash-flow timing.

The remainder of the paper is organized as follows. Section 2 provides background on the term structure of equity and real options theory. Section 3 develops the testable hypotheses. Section 4 describes the data and methodology required for the empirical analysis. Section 5 and 6 present the main empirical results. Section 7 concludes.

2 Background

The term structure of equity returns refers to the equity yields across the timing horizon. The formal definition of equity yield is first discussed in section 2.1. Then in section 2.2, I use a reduced form model to illustrate how the real options theory can explain the term structure of equity returns.

2.1 Equity yield

We know from the fundamental asset pricing identity that the risk-return relation of an asset i can be expressed as:

$$\Rightarrow E[Re^i_{t,t+1}] = \beta^{i,M}_{t,t+1}\lambda^M_{t,t+1}, \tag{1}$$

where $E[Re^i_{t,t+1}]$ is the expected excess return for firm i. The expectation is based on the information at time t, but the expectation time subscript is excluded here for convenience; $\beta^{i,M}_{t,t+1}$ is the risk exposure with respect to some risk factor featured by the stochastic discount factor M for firm asset i; $\lambda^M_{t,t+1}$ is the price of the risk with respect to the risk factor. The subscript in this equation indicates the time interval, from time t to $t+1$, in which the expected excess returns is measured.

Equation (1) is for one period only, we can extend it to a longer time horizon:

$$\Rightarrow E[Re^i_{t,t+n}] = \beta^{i,M}_{t,t+n}\lambda^M_{t,t+n}, \tag{2}$$

so that

$$E[1 + Re^i_{t,t+n}] = E[(1 + Re^i_{t,t+1}) \times (1 + Re^i_{t+1,t+2}) \times ... \times (1 + Re^i_{t+n-1,t+n})] \tag{3}$$

and

$$M_{t,t+n} = M_{t,t+1} \times M_{t+1,t+2} ... \times M_{t+n-1,t+n}. \tag{4}$$

We consider $E[Re^i_{t,t+1}]$ as the expected holding period return of a short-term financial asset for firm i that pays out cash flow at time $t+1$ and $E(Re^i_{t,t+n})$ as the expected holding period return of a long-term financial asset for firm i that pays out cash flow at time $t+n$. Then we can define the equity yield for the short- and long-term assets, $Y^i_{t,t+1}$ and $Y^i_{t,t+n}$, as the followings:

$$Y^i_{t,t+1} = E[Re^i_{t,t+1}], \tag{5}$$

and

$$Y^i_{t,t+n} = [E(Re^i_{t,t+n}) + 1]^{\frac{1}{n}} - 1. \tag{6}$$

Formally, the term structure of equity refers to the value of $Y^i_{t,t+n}$ across different n. Although our main interest is the term structure of equity yields, empirically equity yields are not observable and, hence, we use assets' returns as proxies for the equity yields observed in equation (5) and (6).

One way to analyze the term structure of equity is to specify the equity yields in terms of beta representation by combining equation (1) and (5):

$$Y^i_{t,t+1} = E[Re^i_{t,t+1}] = \beta^{i,M}_{t,t+1}\lambda^M_{t,t+1}. \tag{7}$$

Similarly, for the long-term asset:

$$\Rightarrow (1 + Y^i_{t,t+n})^n = 1 + E(Re^i_{t,t+n}) = 1 + \beta^{i,M}_{t,t+n}\lambda^M_{t,t+n}, \tag{8}$$

and if the excess return is small enough, we have an approximation:

$$Y^i_{t,t+n} \simeq \frac{1}{n}E_t(Re^i_{t,t+n}) = \beta^{i,M}_{t,t+n}\frac{\lambda^M_{t,t+n}}{n}. \tag{9}$$

where the risk price $\lambda^M_{t,t+n}$ is divided by the number of periods n to indicate that this is a price for a single period.

van Binsbergen, Brandt, and Koijen (2012) document that the short-term equity yield is larger than the long-term equity yield, that is, $Y^i_{t,t+1} \geq Y^i_{t,t+n}$. Such a finding, according to equation

(7) and (9), must be due to the difference in risk exposure, $\beta^{i,M}_{t,t+1} \geq \beta^{i,M}_{t,t+n}$, or the difference in single period risk price, $\lambda^{M}_{t,t+1} \geq \frac{\lambda^{M}_{t,t+n}}{n}$, or both. Some papers suggest models that feature the risk price channel (Curatola, 2015; Eisenbach and Schmalz, 2016; Andries, Thomas Eisenbach, and Schmalz, 2017), while the others feature the risk exposure channel (Favilukis and Lin, 2016; Ai, Croce, Diercks, and Li, 2012) including this article.

2.2 Real options theory

Having defined the term structure of equity, this sub-section illustrates how real options theory can explain the downward sloping term structure of equity. My model mainly follows Bernardo, Chowdhry, and Goyal (2007), in which the value of any firm i at time t can be decomposed into two components, the value of assets-in-place, A^i_t and the present value of real options G^i_t (see also Chung and Charoenwong, 1991; Berk, Green, and Naik, 1999; Carlson, Fisher, and Giammarino, 2004).

$$V^i_t = A^i_t + G^i_t. \tag{10}$$

Accordingly, the firm's asset beta is simply a weighted average of the beta of assets-in-place and the beta of growth opportunities:

$$\beta^{i,M}_{t,t+n} = \frac{A^i_t}{V^i_t}\beta^{i,A}_{t,t+n} + \frac{G^i_t}{V^i_t}\beta^{i,G}_{t,t+n}, \tag{11}$$

where $\beta^{i,M}_{t,t+n}$ represents the market beta for firm i that corresponds to expected return period t to $t+n$. Similarly, $\beta^{i,A}_{t,t+n}$ and $\beta^{i,G}_{t,t+n}$ represent the beta with respect to assets-in-place and the beta with respect to real options.

Assume the firm's assets-in-place follows the diffusion process:

$$dA^i_t/A^i_t = \mu dt + \sigma dz^i_t, \tag{12}$$

where μ is the expected growth rate of return on assets-in-place, σ is the return volatility, and z^i_t

is a standard Wiener process. The firm's growth opportunity allows it to duplicate the cash flows of the assets-in-place for an investment of I. Assuming that this investment opportunity may be undertaken at some future date $t+T$ and that the risk of the firm's assets-in-place is spanned by the returns on a tradeable asset, the value of the growth opportunity in a frictionless market is given by the Black-Scholes formula:

$$G_t^i = N(d_1)A_t^i - N(d_2)I_t^i e^{-rT} \tag{13}$$

where

$$d_1 = \frac{\ln(A_t^i / I_t^i e^{-rT}) + 0.5(\sigma\sqrt{T})^2}{\sigma\sqrt{T}} \tag{14}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{15}$$

and N(.) is the cumulative distribution function for the standard normal distribution.

The beta of firm's assets-in-place, $\beta_{t,t+n}^{i,A}$, as in equation (11) can be written as:

$$\beta_{t,t+n}^{i,A} = \frac{COV(M_{t,t+n}, R_{t,t+n}^{i,A})}{VAR(M_{t,t+n})} \tag{16}$$

where $R_{t,t+n}^{i,A} = dA_t^i / A_t^i$, and $M_{t,t+n}$ represents the marginal rate of substitution. Similarly, the beta of firm's growth opportunity, $\beta_{t,t+n}^{i,G}$, can be written as:

$$\beta_{t,t+n}^{i,G} = \frac{COV(M_{t,t+n}, R_{t,t+n}^{i,G})}{VAR(M_{t,t+n})} \tag{17}$$

where

$$R_{t,t+n}^{i,G} = dG_t^i / G_t^i. \tag{18}$$

Equation (18) can be rewritten as:

$$\frac{dG_t^i}{G_t^i} = \frac{dG_t^i / dA_t^i}{G_t^i / A_t^i} \frac{dA_t^i}{A_t^i} \tag{19}$$

$$\Rightarrow R_{t,t+n}^{i,G} = \frac{A_t^i}{G_t^i} \frac{dG_t^i}{dA_t^i} R_{t,t+n}^{i,A} \tag{20}$$

Substituting (20) into (17), we can express the beta of the growth option in terms of the beta of assets-in-place:

$$\beta^{i,G}_{t,t+n} = \frac{dG^i_t}{dA^i_t}\frac{A^i_t}{G^i_t}\beta^{i,A}_{t,t+n} \tag{21}$$

Substituting equation (21) into (11), we can express the firm's total risk exposure in terms of the beta of assets-in-place:

$$\beta^{i,M}_{t,t+n} = \frac{A^i_t}{V^i_t}(1 + \delta^i_{t,t+n})\beta^{i,A}_{t,t+n} \tag{22}$$

where

$$\delta^i_{t,t+n} = \frac{dG^i_t}{dA^i_t} \tag{23}$$

Equation (22) states that the total risk exposure of the firm ($\beta^{i,M}_{t,t+n}$) is equal to the risk exposure of the asset-in-place ($\beta^{i,A}_{t,t+n}$), scaled by two multipliers, the market leverage $\frac{A^i_t}{V^i_t}$, and one plus delta, $\delta^i_{t,t+n}$.

2.2.1 Effect of delta

This article suggests that the downward sloping term structure of equity return is mainly due to the delta, $\delta^i_{t,t+n}$, in equation (22). This delta is analogous to one of the financial option greek —delta, which indicates the sensitivity of option value to the change of underlying asset. The value of delta is sensitive to the time-to-maturity (τ). Such sensitivity is measured by a second-order greek, the option charm or delta decay:

$$Charm = -\frac{\partial \delta}{\partial \tau} = -\frac{\partial^2 G}{\partial A \partial \tau}. \tag{24}$$

For an in-the-money option, the shorter the time-to-maturity, the higher the option delta. This happens because the shorter expiration option that is deep in-the-money tends to behave like a stock. Analogously, equation (22) suggests that firm with short-term real options that are soon to be exercised would have higher delta (δ^i), higher risk exposures ($\beta^{i,M}$), and correspondingly higher returns than do another identical firm but with long-term real options, that is, a downward sloping term structure of equity returns.

2.2.2 Effect of beta

So far I have not specified any structure of the stochastic discount factor M, which is crucial in asset pricing models. I assume $M_{t,t+n}$ is a linear function of an aggregate shock $X_{t,t+n}$, so that

$$M_{t,t+n} = 1 - \gamma X_{t,t+n}. \tag{25}$$

This article considers X as the cash flow shock inspired by Campbell and Vuolteenaho (2004). The authors show that the beta with respect to cash flow shock is greatly responsible for the value premium, which is an indirect inference on the term structure of equity returns. I assume that the shock is linear to the time interval, i.e. $X_{t,t+n} = nX_{t,t+1}$, and that the multiple-period return for assets-in-place can approximated by a linear function of single-period return, i.e. $R^{i,A}_{t,t+n} \simeq nR^{i,A}_{t,t+1}$. This assumption can be justified by the fact that assets-in-place generate more stable cash flows growth. Then equation (16) can be rewritten as:

$$\beta^{i,A}_{t,t+n} \simeq \frac{COV(n\gamma X_{t,t+1}, nR^{i,A}_{t,t+1})}{n^2\gamma^2 VAR(X_{t,t+1})} = \beta^{i,A}_{t,t+1}. \tag{26}$$

Equation (26) says that beta with assets-in-place remains the same over different time interval, and hence is not responsible for the downward sloping term structure pattern.

2.2.3 Effect of operating leverage

Operating leverage is known to be essential in asset pricing (Lev, 1974; Novy-Marx, 2011; Taussig and Akron, 2017). Some papers suggest that the operating leverage is responsible for the downward sloping term structure pattern (see Favilukis and Lin, 2016; Marfe, 2015). In these papers, firms' operating leverage, in the form of either physical capital or labor, is difficult to adjust in the short-run, so that firms are more vulnerable when faced with negative shocks. I conduct a robustness check for this channel in the next section.

3 Hypothesis development

The existing literature has suggested various models that generate facts on the term structure of equity. This section develops testable hypotheses that distinguish real options theory from other models.

In sum, the real options theory states that short-term real options are more sensitive to aggregate shock than do long-term options, because short-term options are soon to be exercised, and converted into assets-in-place, which are fully exposed to aggregate shocks. As a result, short-term equities, which carry short-term real options, are riskier and earn higher returns than long-term equities, which carry long-term real options.

The first hypothesis tests whether long-term (short-term) equities are associated with long-term (short-term) real options. The short-term real options considered here should be "in-the-money", because only the options that are close to being exercised would be riskier in the short-term than in the long-term. How can we identify such short-term real options that are soon to be exercised? We can look at firms' near future investment. The idea is as follows. Real options allow firms to choose when to invest in potential projects, but ultimately the firms need to realize the project through real investments, analogous to exercising real options. Moreover, the shorter (longer) the maturity of real options, the higher (lower) the investment in near future. This implies the following:

Hypothesis 1 *If the short-term firms are associated with more short-term real options that are close to being exercised, then the short-term firms would have higher near future investments.*

The second hypothesis tests the relation between risks and returns. The real options theory emphasize that the return difference between long- and short-term assets is due to risk exposures (I will discuss further about the risk measure in the next section). This implies:

Hypothesis 2 *If the term structure of equity returns is driven by the corresponding risk exposure, then, the term structure of equity returns should align with the corresponding betas.*

In the existing literature, most of papers focus only on the term structure on aggregate level. Although various theories have been proposed, without further restrictions it would be difficult to pin down the true underlying mechanism that drives the term structure of equity returns. One of the meaningful restrictions could be the cross-sectional pattern. Cross-sectional firms differ in terms of their composition of real options relative to assets-in-place. Correspondingly, their term structures of returns would also differ. How the term structures differ across different firms depends on which risk channel drives the phenomenon. The true mechanism should incorporate the empirical pattern on both the aggregate and cross-sectional level. Therefore, looking for empirical evidence from the cross section can help distinguish among various explanations. The remainder of the hypotheses focus on the cross-sectional implications:

Hypothesis 3A *If the real options mechanism is true, firms with a larger fraction of real options in their firm values should exhibit a steeper downward sloping term structure of equity returns.*

Combining hypothesis 2 and 3A leads to:

Hypothesis 3B *If the real options mechanism is true, firms with a larger fraction of real options in their firm values should exhibit a steeper downward sloping term structure of betas.*

In addition to real options theory, another strand of theories that supports the risk exposure channel concerns operating leverage. For example, Favilukis and Lin (2016) and Marfe (2015) argue that wages are sticky in the short- run, therefore, productivity shock would be mostly absorbed by the short-term dividends that become highly volatile. In the long-run, however, wages are adjustable, which can share some burden of the productivity shock, reducing the risk of the dividends. This theory instead implies the following hypotheses that are exclusive of hypotheses 3A and 3B:

Hypothesis 4A *If the operating leverage mechanism is true, firms with larger fraction of assets-in-place in their firm values should exhibit a steeper downward sloping term structure of equity returns.*

Hypothesis 4B *If the operating leverage mechanism is true, firms with larger fraction of assets-in-place in their firm values should exhibit a steeper downward sloping term structure of cash flow betas.*

There are also other mechanisms that emphasize the risk price channel, which suggest that the term structure of equity returns is downward sloping because short-term assets have higher risk prices than long-term assets. These models, however, have no cross sectional implications, given that the law of one price holds. Accordingly I hypothesize the following:

Hypothesis 5A *If the risk price channel is the only channel that explains the term structure of equity returns, all cross-sectional stocks should exhibit the same downward sloping term structure of equity returns.*

Hypothesis 5B *If the risk price channel is the only channel that explains the term structure of equity returns, all cross-sectional stocks should exhibit the same downward sloping term structure of cash-flow betas.*

4 Data and Methodology

This section sets up the empirical tools required to test the hypotheses. Section 4.1 describes the data used in my test. Section 4.2 describes how I construct the term structure of equity using the measure of equity duration, which is the key variable that distinguishes the assets across the timing horizon.

4.1 Data

I use all NYSE, Amex, and NASDAQ nonfinancial firms (excluding firms with four-digit SIC codes between 6000 and 6999) listed on the CRSP monthly stock return files and the Compustat annual industrial files. My sample period covers the period from June 1968 to Dec 2015, to ensure a reasonable number of firms in each month, particularly in the earlier part of the sample. To mitigate backfilling biases, a firm must be listed on Compustat for two years before it is included in the data set (Fama and French, 1993). To minimize the impact of outliers, I winsorize all variables at the 1% and 99% levels.

To account for the delisting bias in the CRSP database, I follow Beaver, McNichols, and Price (2007) to incorporate those delisted returns into the monthly return data. Delisting data are recorded in the daily CRSP database. To ensure that the exact delisting date can be identified, I include only the observations with a delisting code greater than 199. If the delisting date is the last day of the month, the delisted return is set as the replacement value, which is equal to the average delisted returns across all delisted firms with the same delisting code. If the delisting falls mid month, the delisted return is equal to the last monthly CRSP return compounded with replacement value.

At the end of June of each year t, I use NYSE breakpoints to split stocks into portfolios based on firm characteristics, and calculate monthly portfolio returns and the corresponding betas from July of year t to June of t +1. The definition of the firm characteristics is detailed in Appendix. The five Fama & French factors and the one-month Treasury- bill rate comes from the Fama & French data library on Ken French's webpage. The data for the interest rate surprise is downloaded from Kenneth Kuttner's webpage.

4.2 Methodology

Empirical identification for the term structure of equity typically involves a comparison between the returns of long- and short-term equities. For example, van Binsbergen, Brandt, and Koijen (2012) extract dividend strips of the market index from the options data. The dividend strips , considered short-term equities, are then compared with the market index, considered long-term equity. This approach, however, is not feasible in my case because financial derivatives for individual stocks are not commonly traded. Therefore, I choose to use the cross sectional data in the spirit of Weber (2016). Specifically, I construct the cash-flow-duration following Dechow, Sloan, and Soliman (2004), which resembles the traditional Macaulay duration for bonds, and reflects the weighted average time to maturity of cash flows. The stock returns across the cash-flow-duration inform about the term structure of equity yields. The advantage of this empirical method is that it can be easily applied to cross section to test the mentioned hypotheses. For example, I can study the term structures of returns for the firms with different growth characteristics by double-sorting the sample with duration and book-to-market ratio.

4.2.1 Duration

The cash flow duration is defined as:

$$DUR_{i,t} = \frac{\sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{P_{i,t}} \tag{27}$$

where $DUR_{i,t}$ is the duration of firm i at the end of fiscal year t, $CF_{i,t+s}$ denotes the cash flow at time $t+s$, $P_{i,t}$ is the current price, and r is the expected return on equity, which is assumed to be a constant.

Formula (27) cannot be directly used, however, as stocks do not have a well-defined finite maturity, $t+T$, as do bonds. To address this, we can split the equation into two parts - a finite detailed forecasting period and an infinite terminal value:

$$DUR_{i,t} = \frac{\sum_{s=1}^{T} s \times CF_{i,t+s}/(1+r)^s}{P_{i,t}} + (T + \frac{1+r}{r})\frac{P_{i,t} - \sum_{s=1}^{T} CF_{i,t+s}/(1+r)^s}{P_{i,t}}. \tag{28}$$

Formula (28) is computable if cash flow in the first term could be accurately forecasted, and the second term is assumed to pay out as a level perpetuity.

To forecast cash flow, we start with the following accounting identity:

$$CF_{i,t+s} = E_{i,t+s} - (BV_{i,t+s} - BV_{i,t+s-1}), \tag{29}$$

which says that cash flow to equity for a firm i at each period $t+s$ is equal to the firm's accounting earning at the end of fiscal year $t+s$, $E_{i,t+s}$, minus any change of book value of equity over the year $t+s$, $BV_{i,t+s} - BV_{i,t+s-1}$. Re-arranging the right-hand side of equation (29) gives:

$$CF_{i,t+s} = BV_{i,t+s-1} \times [\frac{E_{i,t+s}}{BV_{i,t+s-1}} - \frac{BV_{i,t+s} - BV_{i,t+s-1}}{BV_{i,t+s-1}})]. \tag{30}$$

Now, the two fraction terms in the bracket of equation (30), return on equity (ROE), $E_{i,t+s}/BV_{i,t+s-1}$, and the growth in book equity, $(BV_{i,t+s} - BV_{i,t+s-1})/BV_{i,t+s-1}$, are forecastable if we assume them stationary. I model ROE as a first-order autoregressive process with an autocorrelation coefficient of 0.57 and a long-run mean of 0.12, and the growth in book equity as a first-order autoregressive process with an autocorrelation coefficient of 0.24 and a long-run mean of 0.06. These parameter values are taken from Dechow et al. (2004). For the starting year (t =0), I measure ROE as income before extraordinary items (item IB) divided by one-year-lagged book equity (item CEQ) and the book equity growth rate as the annual change in sales (item SALE). Finally, I use a forecasting period of $T = 10$ years and a cost of equity of $r = 0.12$.

4.2.2 Orthogonalization

The measure of DUR ideally should capture the "time-to-maturity" of equity cash flows. However, by definition, DUR is scaled by the market price, meaning that DUR is likely to be correlated with the other price ratios such as BM. Such correlation is problematic in a ranking exercise, because the rank, based on duration, might unintentionally capture the rank of valuation ratio rather than time-to-maturity. Therefore, it is important to purge the DUR from the price effect before the measure is put into use. The price ratio that I refer to is not necessarily the BM ratio, but I use BM for the remainder of analysis because BM is the most prominent price ratio in the literature.

Specifically, the correlations between BM and DUR in the panel data could exist in two ways: cross sectional and time series. We are concerned with time series correlation for each firm because the level of a firm's DUR might reflect a particularly large or small valuation that is specific to some firm-wise or industry-wise characteristics. We are also concerned with cross-sectional correlation at each time. The problem happens when a group of stock prices are moved by some idiosyncratic shock so that the cross-sectional distribution of the firms along the DUR dimension is distorted. This problem, however, is considered less severe because the effect of the idiosyncratic shock should be (largely) cancelled out at the portfolio level. In the event of aggregate shock to the prices, the whole cross sectional distribution would be shifted by the same amount so that the rank of DUR would remain the same.

To solve correlation problem, I extract the DUR measure information that is orthogonal to the price effect. The relation between DUR and BM can be considered as:

$$DUR_{i,t} = a + b_1 BM_{i,t} + b_2 DUR^r_{i,t} + \xi_{i,t}, \tag{31}$$

where $DUR^r_{i,t}$ is a duration component that is orthogonal to the BM ratio. I extract the orthogonal information by estimating DUR^r in equation (31). Specifically, I use a two-stage orthogonalization procedure as follows. First, I run a cross-sectional regression of DUR on BM for each period t:

$$DUR_{i,s} = a + b_1 BM_{i,s} + \varepsilon_{i,s}, \quad \forall s = t. \tag{32}$$

Second, I run a time series regression of the residuals from the first stage regression, $\varepsilon_{i,t}$, on the explanatory variable again for each firm i with its whole history of data:

$$\varepsilon_{j,t} = a + b_1 BM_{j,t} + \xi_{j,t}, \quad \forall j = i. \tag{33}$$

The residual ξ obtained in the second stage regression is used as my main measure for cash flow duration (DUR^r), which is referred to as the "orthogonalized duration" for the remainder of this article unless specified otherwise.

5 Empirical analysis

This section reports the empirical test results. Section 5.1 provides the summary statistics. Section 5.2 shows that the stock returns align with the corresponding risk exposures across the timing horizon. Section 5.3 and 5.4 repeat the same exercise but for different portfolios sorted by various firm characteristics, including book-to-market ratio, profitability ratio, sales growth and operating leverage. Section 5.5 discusses some implications related to portfolio trading strategies.

5.1 Summary Statistics

Table 1 reports the summary statistics for the portfolios sorted by unorthogonalized duration in Panel A, and orthogonalized duration in Panel B. The first row of Table 1A shows that the monthly value-weighted returns averaged over the year 1968 to 2015 are monotonically decreasing in the unorthogonalized duration, and the return spread between short- and long-unorthogonalized duration stocks is 0.37% per month, significantly different from zero. This suggests that the term structure of equity is downward sloping, consistent with Weber (2016). This interpretation, however, can be problematic because the duration spread can be due to the valuation effect or simply the book-to-market characteristics: the book-to-market ratios are monotonically decreasing in unorthogonalized duration as shown in the second row of Table 1A. In other words, if the book-to-market ratio and duration are perfect proxies for each other, the duration spread might simply capture the value premium instead of term premium (Lettau and Wachter, 2007), then the discussion about term structure of equity here would be obsolete. Fortunately, this is not the case: DUR and BM seem to contain different information evidenced by the fact that growth stocks (low book-to-market stocks) do not necessarily have higher future cash-flow growth rates than the value stocks (Chen, 2014). Moreover, the firm level correlation between DUR and BM is low (not reported here). Therefore, it is meaningful to extract the information from duration that is truly relevant to cash flow timing. Disentangling DUR from BM by orthogonalization as in section 4.2, thus, becomes particularly important in my analysis. With the orthogonalized duration, we see from Table 1B that the return spread between short- and long-orthogonalized duration stocks remains significant with 0.61% per month, but the book-to-market ratio is no longer monotonic in duration, which makes sure that the relation between return and orthogonalized duration is not driven by the BM ratio. These results justify the use of orthogonalized duration as a measure of cash flow timing.

We are concerned about the information content of the duration measure after the orthogonalization procedure. To check the robustness of this measure, I compare the interest rate sensitivity for portfolios sorted by the orthogonalized and unorthogonalized duration. If the orthogonalized duration properly captures the information about cash-flow timing as what the unorthogonalized duration does, then the post-announcement returns in response to an increase in interest rate should be more negative for long-orthogonalized duration stocks than for short-orthogonalized duration stocks.

Specifically, using panel data, I conduct an event study by regressing the 5 days average market-adjusted returns on the interest rate surprise after the FOMC meeting for each duration portfolio [3]. The interest rate surprise is estimated with the method proposed by Bernanke and Kuttner (2005) [4]. The event date t is the announcement date of the FOMC meeting, while the post-event date window is from $t+1$ to $t+6$. The thrid rows of the two panels in Table 1 reports the regression coefficients, which indicate the interest rate sensitivities. For example, the interest rate sensitivity of the shortest unorthogonalized duration stocks is 0.14, implying that a one percentage increase of interest rate is followed by a 0.14% increase of 5 days average portfolio returns adjusted by the market return; the interest rate sensitivity of the longest unorthgonalized duration stocks is -0.56, implying that a one percentage increase of interest rate is followed by a 0.56% decrease of 5 days average portfolio returns adjusted by the market return. This result suggests that the unorthogonalized DUR measure successfully captures the cash-flow timing property. The main point is that the pattern of interest rate sensitivity remains decreasing in the duration after orthogonalization, suggesting that the DUR^r captures the cash-flow timing property just as well.

5.2 Univariate Analysis

To test hypothesis 1 I sort the firms into 10 deciles using the orthogonalized duration, and check whether the short-term future investments are decreasing in duration. The investment at time t is measured by abnormal corporate investment (ACI), defined as the capital expenditure at time $t-1$ divided by the three years average of capital expenditure from $t-2$ to $t-4$ minus one (Titman, Wei, and Xie, 2004). The detailed definition of this measure can be seen in the appendices. Abnormal

[3] It has been shown that the stocks prices react strongly to FOMC announcement (Savor and Wilson, 2013, 2014)

[4] The data for the interest rate surprise is downloaded from https://econ.williams.edu/faculty-pages/research/

investment is used because I am interested in the investment activities that are related to the new business projects rather than the regular investment activities that are related to capital replacement of existing assets. Table 2 reports the equally weighted averages of lead abnormal investments three years into the future. We see that future abnormal investments are higher for short-duration stocks, and monotonically decreasing in duration. This result is consistent with the claim that short-duration stocks have more short-term real options to be exercised soon, which induce more near future investment activities.

To test hypothesis 2, I show that the monotonic pattern of stock returns across duration is driven by their risk exposures. A natural candidate of risk measure is the market beta, which however has been criticized for its empirical performance in terms of explaining the cross-sectional returns Fama and French (1993). van Binsbergen et al. (2012) also show that the short-term equity does not have a higher beta to justify its return. A potential problem with the market beta is the measurement error, in the sense that the traditional way of constructing the market beta with past returns might not be appropriate. One solution is to use an alternative measure such as the cash-flow beta.

My motivation for studying the cash-flow beta is inspired by Campbell and Vuolteenaho (2004), who derive a version of ICAPM that decomposes risk premiums into two components, namely the part attributed to cash-flow risk and the other part attributed to discount rate risk. They argue that "these two components should have different significance for a risk-averse, long-term investor who holds the market portfolio. Such an investor may demand a higher premium to hold assets that co-vary with the market's cash-flow news than to hold assets that covary with news about the market's discount rates, for poor returns driven by increases in discount rates are partially compensated by improved prospects for future returns." It has shown that the cash-flow beta has been successful in explaining various cross-sectional anomalies Cohen et al. (2009). This paper argues that the cash flow beta is able to explain the returns across different maturity as well: the short-term stocks have higher cash-flow betas because their embedded short-term real options are more sensitive to the cash-flow shock.

Table 2 reports the cash-flow betas for the decile portfolios sorted by orthogonalized duration.

Within each of the single-sorted portfolio, I compute the cash-flow beta using the direct measurement approach detailed in the appendix. We see that the cash-flow betas are monotonically decreasing in duration, aligned with the return pattern. The beta spread between the two extreme portfolios is 0.53, significantly different from zero. This result suggests that the portfolio returns can be driven by their risk exposures measured by cash-flow betas. In addition to the cash-flow betas, I also look at the patterns of discount rate betas across the decile portfolios. I find that the discount rate betas are not responsive to the duration, suggesting that discount rate risk cannot justify the term structure of equity.

5.3 Bivariate Analysis

This section aims at testing the three set of mutually exclusive hypotheses 3 to 5, which requires investigating the term structure of returns on cross sectional level. Specifically, I conduct a double-sorting by cash-flow-duration DUR^r and a firm characteristic that captures the amount of real options relative to assets-in-place. The idea follows from Weber (2016) in the sense that the portfolio returns across duration mimics the equity yields across different maturities, which can be considered as a representation of term structure of equity. My test differs from Weber (2016) in the sense that I look at the term structure of equity separately for different portfolios sorted by firm characteristics. One meaningful proxy for the relative amount of real options versus assets-in-place is the book-to-market ratio (BM). Low BM firms are considered firms with more real options, while the high BM firms are considered firms with more assets-in-place. This empirical setting allows us to study the hypotheses 3A, 4A and 5A at the same time with the following implications. The real options theory predicts that low BM firms will exhibit a steeper downward sloping term structure of returns according to hypothesis 3A; the operating leverage channel predicts that high BM firms will exhibit a steeper downward sloping term structure of returns according to hypothesis 4A; finally the risk price channel predicts that both the low and high BM firms will exhibit the same downward sloping term structure of returns according to hypothesis 5A.

Table 3A reports the value weighted returns for the 5-by-5 portfolios for the period 1968 to

2015. The portfolios are organized in a square matrix with growth stocks at the top, value stocks at the bottom, short orthogonalized duration stocks at the left, and long orthogonalized duration stocks at the right. At the right edge of the matrix, I report the differences between the short- and long-duration portfolios for each BM group. Along the bottom edge of the matrix, I report the differences between the value and growth stocks for each duration group. T-statistics are reported in parentheses. The main observation is that the spread between long-duration growth stocks and short-duration growth stocks in the first row is significantly negative (-0.91% per month), that is, the short-duration growth stocks earns a much higher return than do the long-duration growth stocks. In other words, the term structure of returns for growth stocks is downward sloping. Conversely, the duration spread for the value stocks in the fifth row is insignificantly different from zero, implying that the term structure of returns for value stocks is flat. These results support hypothesis 3A rather than hypothesis 4A: the term structure of equity is driven by the effect of real options, but not the operating leverage.

This result also automatically rejects hypothesis 5A, because my finding that the downward sloping term structure of returns varies in the cross section suggests that the underlying driving mechanism must involve some cross-sectional heterogeneity in terms of the risk exposures. Note that since the growth stocks have steeper downward sloping term structure of returns, mechanically the value premium is stronger among the long-duration stocks. The value strategy earns an average monthly return of 0.88% for the longest duration quintile, but -0.20% for the shortest duration quintile. In other words, the term structure of value premium is upward sloping.

To test hypotheses 3B, 4B and 5B, I compute the cash-flow betas for each of the double-sorted portfolios. The idea is to verify whether the term structure of betas aligns with the term structure of returns for each BM portfolio. Table 3B shows that the cash-flow betas are generally decreasing in DUR^r across the columns, which is in line with the monotonic patterns of the stock returns in Table 3A. The spreads in betas between the long and short DUR^r portfolios are strongest for the growth stocks in the first row which equals -1.15, but is marginally positive for the value stocks in the fifth row. This result supports hypothesis 3B against hypotheses 4B and 5B, again consistent with real options theory. Moreover, the alignment of returns and betas within subsamples further supports hypothesis 2: the term structure of equity is driven by the risk exposures of cash-flow shock. Table 3C repeats the same exercise but with the discount rate betas. We see that the discount rate betas have almost no effect in explaining the term structure of equity for both value and growth stocks. The beta spread between long- and short-duration stocks are insignificant for all five groups of BM portfolios.

5.4 Robustness

5.4.1 Firm characteristics

To show that the return patterns found in table 3A are not driven by firm characteristics, I compute the BM ratio for each of the double-sorting portfolios. Table 4 shows that the BM ratio stays constant across the duration for each BM portfolios, except for the value stocks. which suggests that the monotonic relation between portfolio returns and duration is not driven by firm characteristics even within subsamples.

5.4.2 Alternative proxies for real options

We are concerned that the BM ratio might not be a proper measure for real options embedded in the firms. This section repeats the analysis with alternative proxies for real options, including the profitability and sales growth. Specifically, I repeat the double sorting exercise but with profitability, measured by the gross-profit-to-asset ratio (GPA) and orthogonalized duration as my sorting variables.

High profitability stocks should exhibit a steeper downward sloping term structure of returns than low profitability stocks. The intuition is that these profitable firms have more internal cash flows at a lower cost of capital, which allows the firms more flexibility on investments when facing negative shocks (Hackbarth and Johnson, 2015). [5] Table 5A shows that profitable stocks exhibit a downward sloping term structure of returns. (the short-duration profitable stocks earns 0.84% of

[5] Profitable stocks are also growth stocks (Novy-Marx, 2013).

return higher than the long-duration profitable stocks), while stocks with low profitability exhibit a flat term structure of returns (the return difference between long- and short-duration unprofitable stocks is not significantly different from zero). Correspondingly, the profitable stocks have a steeper downward sloping term structure for cash-flow betas than do the unprofitable stocks as shown in Table 5B (the beta spread between short- and long-duration profitable stocks is 1.0, while that between short- and long-duration unprofitable stocks is not significantly different from zero).

Then, I also use sales growth (SG) as a proxy for real options following Grullon, Lyandres, and Zhdanov (2012), who argue that an increase in sales (and production) in the future is likely to be caused by the future exercise of real options. I again repeat the double-sorting exercise by DUR^r and SG. Table 6A shows that the stocks with high SG exhibit a the downward sloping term structure of returns (the return difference between short- and long-duration for the high SG quintile is 0.79%), while stocks with low SG exhibit a flat term structure of returns (the return difference between short- and long-duration for the high SG quintile is not significantly different from zero). Correspondingly, the stocks with high SG have a steeper downward sloping term structure of cash-flow betas (the beta difference between short- and long-duration for the high SG quintile is 0.70), than do the stocks with low SG shown in Table 6B (the beta difference between short- and long-duration for the low SG quintile not significantly different from zero). In summary, these findings support hypotheses 3A and 3B, consistent with the real options theory.

5.4.3 Alternative proxies for assets-in-place

As a robustness check for 4A and 4B, I repeat the double-sorting exercise but with operating leverage (OL), and orthogonalized duration as my sorting variables. Table 7 shows that the term structures of returns for all the operating leverage quintiles are downward sloping, but the return spread between long- and short-duration stocks is larger for the low operating leverage stocks than for the high operating leverage stocks, that it, the low operating leverage stocks exhibit a steeper downward sloping term structure pattern, which, however, is inconsistent with hypothesis 4A. Correspondingly, the term structures of cash-flow betas for these operating leverage quintiles are also downward sloping in general, but none of them exhibit a steeper pattern than the others. These results rejects the operating leverage channel.

5.4.4 Alternative measure of duration

The duration defined in equation (28) uses an unrealistically fixed discount rate r. Ideally, we should discount future cash flows with discount rates that correspond to different maturity of cash flows. However, equity duration is a forecasting variable, that is, both the cash flows and discount rates are not deterministic. By using a single discount rate for all the cash flows with different maturity, equation (28) essentially assumes the term structure of interest rate is flat in the future, which is a simplified but reasonable forecast. Another problem is that the discount rate is fixed over time. Obviously, the discount rate should be time varying, but using a fixed discount rate in equation (28) does not matter in my case, because the discount rate is the same for all firms at each point in time no matter what discount rate is used, and hence it does not affect the ranking of firms by duration. The problem happens with the orthogonalization procedure, which involves the time series of duration, and we are concerned that using a fixed discount rate might not be accurate.

This section relax the assumption by allowing time-varying discount rate, for which I use the 1-year treasury bill as a proxy. Table 8 repeats the exercise of Table 3 except that the duration is computed with time-varying discount rate. We see that portfolio returns are generally decreasing across durations except for the value stocks. This result again suggests that the term structure of equity returns is downward sloping for the growth stocks, but flat for the value stocks, consistent with Table 3. The return spread, however, is weaker than that in Table 3: the short-duration growth stocks earn only 0.22% higher of return than the long-duration growth stocks. The difference between the long- and short-duration value stocks are insignificantly different from zero.

5.5 From the perspective of anomalies

In all the tests above, our main focus in on the portfolio returns across duration. For example, we read Table 3 row-by-row, and interpret the rows as the term structures of returns for stocks with different BM ratio. This section shifts the focus to columns, which essentially shows the spread between the value and growth stocks, that is, value premium, for each duration. It is well known that value stocks have higher returns than growth stocks in general (Fama and French, 1992). The fact that the term structure of returns for growth stocks is downward sloping, and value stocks is flat mechanically implies that the value premium would be stronger for long-term stocks than for short-term stocks, that is, with an upward sloping term structure for the value premium. This observation can also be consistent with the classic interpretation of real options in terms of asset pricing (Cooper, 2006).

In the classic view, real options allow more flexibility for firms to choose when and how to invest (or disinvest). Firms would choose to invest (or disinvest) only if the net present value (NPV) from doing so exceeds the option value of waiting. As a result, there exists a region of firm value within which the firms would not react to aggregate shocks, i.e. these firms have less aggregate risk sensitivity, and earn lower returns. The value premium arises because the growth stocks have more real options, that is insensitive to the aggregate shocks. This effect should be stronger for the long maturity stocks, because the long-term growth firms would be even more flexible in time, in the sense that they do not need to commit to the new projects immediately, but take time to evaluate the potential projects carefully before any real investments. Consequently, the value premium is larger for long-term stocks.

Table 3 already shows that the value premium can differ a lot between the short- and long-duration stocks. It would be interesting to see how other important anomalies perform. I replicate the Fama and French (2015)'s factors, separately, for long- and short-duration groups. Specifically, I assign firms to a set of 2x3x2 portfolios independently sorted by duration, firm characteristics of interest, and size. The DUR breakpoint is the NYSE median duration, $Size$ breakpoint is the NYSE median market cap, and the break points for BM, OP and Inv are the 30th and 70th percentiles within the NYSE stocks sample. Then I construct the SMB, HML, RMW and CMA factors using only the firms within each duration group. The value factor, HML, is the high BM portfolio returns minus the low BM portfolio returns, where the high BM portfolios are the average of the large high BM and small high BM, and the low BM portfolios are the average of the large low BM and small low BM. The profitability and investment factors, RMW and CMA, are constructed in the same way as HML except the second sort is either based on operating profitability (robust minus weak) or investment(conservative minus aggressive). The 2x3 sorts used to construct HML, RMW and CMA produce three Size factors, $SMB_{B/M}$, SMB_{OP} and SMB_{Inv}, which are computed as an average of the three large portfolio returns minus the average of the three small portfolio returns. The size factor SMB from the three 2x3 sorts is defined as the average of $SMB_{B/M}$, SMB_{OP}, and SMB_{Inv}.

Figure (1) plots the time series of the accumulated portfolio returns using portfolio strategies based on the above anomalies. For example, the top-left graph in the figure plots the portfolio value of $1 invested in a long-duration HML, a short-duration HML and the (Fama and French, 2015)'s regular HML starting from July 1968. As we see, the long-duration HML strategy performs much better than the short-duration HML strategy; the regular HML strategy lies between the long and short HML. Similarly, I compare the performance for portfolios based on other strategies. The profitability strategy, RMW, performs better using short-duration stocks than long-duration stocks as we already know. The investment strategy ,CMA, and the size strategy SMB performs better using long-duration stocks than short-duration stocks. High investment firms are considered having more real options and hence earns lower returns, such effect is again stronger in long-term, and hence the investment premium is stronger for long-duration stocks. The relation between firm size and real option is controversial, but my result is consistent with the hypothesis that large firms possess more real options. As the real option effect become stronger at long horizon, the size premium becomes larger for long-duration stocks as well.

6 Asset pricing test

The real options theory should be considered complementary to the other explanations mentioned in section 2.2, but it would be interesting to see how much of the term structure pattern can be accounted for by the real options effect. Specifically, we want to know how much of the duration spread is explained by the variation in cash-flow betas across the timing horizon. To do so, I evaluate the performance of a two-factor model similar to Campbell and Vuolteenaho (2004) that features cash-flow and discount rate betas. The model is first estimated with the following cross sectional regression:

$$\overline{R_i - R_f} = \alpha + \lambda_{CF}\widehat{\beta}_{i,CF} + \lambda_{DR}\widehat{\beta}_{i,DR} + \epsilon_i, \tag{34}$$

where $\overline{R_i - R_f}$ is the average excess returns over time for portfolio i; $\widehat{\beta}_{i,CF}$ and $\widehat{\beta}_{i,DR}$ are the cash-flow and discount rate betas for the portfolio i estimated from the direct measurement approach, and λ_{CF} and λ_{DR} are the price of cash-flow risks and the price of discount rate risk. My tested assets include 10 portfolios single-sorted by BM ratio and 10 portfolios single-sorted by duration.

My estimation differs from Campbell and Vuolteenaho (2004) in two ways. First, I allow the price of discount rate risk to be freely estimated, while Campbell and Vuolteenaho (2004) assumes that price of the discount rate risk is restricted. [6] Their assumption is based on that the elasticity of intertemporal substitution equals one with recursive preference. This assumption, however, can be relaxed so that the price of discount rate risk can be estimated freely (see the appendix for detailed derivation). Second, the values for the cash-flow and discount rate betas are computed using the direct measurement approach in this paper, in contrast to those computed using the VAR method in Campbell and Vuolteenaho (2004).

Table **??**A reports the estimated parameter for the two prices of risks, λ_{CF} and λ_{DR} with their t-statistics. The price of cash-flow risk is 0.39% per month, significantly different from zero, while the price of discount rate risk is 0.33% per month, not significantly different from zero. The last column of table 9A shows that the R^2 of the regression (34) are over 50%, which suggests that the cross sectional variation in the cash-flow and discount rate betas can explain over 50% of the cross-sectional variation in returns with the estimated risk prices.

Table 9B compares the realized and predicted return spreads for both the BM and DUR^r

[6] In Campbell and Vuolteenaho (2004), the price of price of cash-flow risk is γ times the price of discount rate risk, where γ represent the parameter of risk aversion.

deciles. The predicted return spread is estimated from the two factor model as in equation (34). The statistics are organized as follows. The first column indicates the sorting variables, the second column shows the realized return spread between the extreme portfolios sorted by the variable in the first column. The third column shows the predicted return spread implied from the two-factor asset pricing model. The fourth column shows the ratio of the predicted return spread over the realized return spread, indicating the fraction of the return spread that can be explained by the two-factor model. We see that the model can explain over 68% of the cross-sectional variation in DUR^r, and 79% of the variation in BM. Such simple two stage regression implicitly assumes a constant prices for risks. The finding that my two-factor model explains a large fraction of duration premium even with the risk prices fixed implies that the risk exposures, rather than risk prices, are important driving forces for the term structure of equity returns.

As a robustness check, I also conduct the same asset pricing test using the 5-by-5 portfolios sorted by DUR^r and BM ratio as the tested assets. Table 10A reports the estimated prices of risks, and Table 10B compares the realized and predicted return spread between the short- and long-duration portfolios for each BM quintile. We see that the model can explain about 47% of the duration spread for portfolios with lowest BM ratio, where the return spread is the largest. The model maintains the explanatory power for the rest of the portfolios except for the second highest quintile. This results again suggests that my two-factor model explains a large fraction of the duration premium even within subsamples. The lower explanatory power for the the high BM portfolios are relatively unimportant because these portfolios exhibit minimal duration spreads, which can give large errors even with small deviations from the prediction.

7 Conclusion

This article makes two major contributions to the literature. First, I note that the real options theory can be one explanation for the downward sloping term structure of equity returns. The real options theory implies some testable implications for the term structure of equity in cross-section. Second, this article proposes a simple empirical approach to study the term structure of equity returns in cross-section. I document some novel empirical findings: 1) the firms with low BM ratio, high profitability and high sales growth have steeper downward sloping term structure of equity; 2) the term structure of equity returns align with their corresponding risk exposures measured by the cash-flow betas. These results are consistent with the real options theory.

Appendices

A Variable Definitions

ME . The size of a firm used for portfolio formation in year t is simply its market capitalisation (ME) at the end of June of year t.

BM . The book-to-market (BM) ratio of year t is defined the book equity for the fiscal year ending in calendar year t-1 over the market equity as of December t-1, where book equity (BE) as total stockholders' equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stock. Based on availability, I use the redemption value, liquidation value, or par value (in that order) for the book value of preferred stock. I prefer the shareholders' equity number as reported by Compustat. If these data are not available, I calculate shareholders' equity as the sum of common and preferred equity. If neither of the two are available, I define shareholders' equity as the difference between total assets and total liabilities.

OP . Operating profit(OP) is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity.

Inv . Asset growth (IA) is used as a proxy for investment (Inv). IA is computed as the change in total assets (Compustat annual item AT) from the fiscal year ending in year t-2 to the fiscal year ending in t-1, divided by t-2 total assets.

SG . Following Lakonishok, Shleifer, and Vishny (1994), we measure sales growth (SG) in June of year t as the weighted average of the annual SG ranks for the prior 5 years, 5 j=1 (6-j)ŒRank(t-j). The SG for year t-j is the growth rate in sales (COMPUSTAT annual item SALE) from fiscal year ending in t-j-1 to fiscal year ending in t-j . Only firms with data for all 5 prior years are used to determine the annual SG ranks. For each year from t-5 to t-1, we rank stocks into deciles based on their annual SG, and then assign rank i (i =1,...,10) to a firm if its annual SG falls into the ith decile. At the end of June of each year t , we use NYSE breakpoints to assign stocks into deciles based on SG, and calculate monthly value-weighted decile returns from July of year t to June of t +1.

GPA . Following Novy-Marx (2013), we measure gross profits-to-assets (GP/A) as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS) divided by total assets (item AT, the denominator is current, not lagged, total assets). At the end of June of each year t , we use NYSE breakpoints to sort stocks into deciles based on GP/A for the fiscal year ending in calendar year t-1. Monthly value-weighted decile returns are calculated from July of year t to June of t +1, and the deciles are rebalanced in June of t +1.

ACI . Following Titman,Wei, and Xie (2004), we measure ACI at the end of June of year t as $CE_{t-1}/[(CE_{t-2} + CE_{t-3} + CE_{t-4})/3] - 1$, in which CE_{t-j} is capital expenditure (Compustat annual item CAPX) scaled by sales (item SALE) for the fiscal year ending in calendar year $t - j$. The last 3-year average capital expenditure is designed to project the benchmark investment at the portfolio formation year. We exclude firms with sales less than 10 million dollars. At the end of June of each year t , we use NYSE breakpoints to sort stocks into deciles based on their ACI. Monthly value-weighted decile returns are computed from July of year t to June of t +1.

B Aggregate VAR

In specifying the aggregate VAR, we follow Campbell and Vuolteenaho (2004) by choosing the same four state variables. Consequently, our VAR specification is one that has proven successful in cross-sectional asset pricing tests. However, we implement the VAR using annual data, rather than monthly data, in order to correspond to our estimation of the firm-level VAR, which is more naturally implemented using annual observations.

B.1 State variables

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j r_{t+1+j} \tag{35}$$

$$= N_{CF,t+1} - N_{DR,t+1} \tag{36}$$

where r_{t+1} is a log stock return, d_{t+1} is the log dividend paid by the stock, Δ denotes a one period change, E_t denotes a rational expectation at time t, and ρ is a discount coefficient. N_{CF} denotes news about future cash flows (i.e., dividends or consumption), and N_{DR} denotes news about future discount rates (i.e., expected returns).

To implement this decomposition, we follow Campbell (1991) and estimate the cash-flow news and discount-rate-news series using a VAR model. This VAR methodology first estimates the terms $E_t r_{t+1}$ and $(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$ and then uses r_{t+1} and equation (1) to back out the cash-flow news.

first estimating the terms $E_t r_{t+1}$ and $(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$ and then using realizations of r_{t+1} and Equation (2) to back out the cash-flow news.

We assume that the data are generated by a first-order VAR model

$$z_{t+1} = a + \Gamma z_t + u_{t+1} \tag{37}$$

where z_{t+1} is an m-by-1 state vector with r_{t+1} as its first element, a and Γ are an m-by-1 vector and m-by-m matrix of constant parameters, and u_{t+1} an is i.i.d. m-by-1 vector of shocks. Of course, this formulation also allows for higher-order VAR models via a simple redefinition of the state vector to include lagged values.

Provided that the process in Equation (20) generates the data, $t + 1$ cash-flow and discount-rate news are linear functions of the $t + 1$ shock vector:

$$N_{DR,t+1} = e1' \lambda u_{t+1} \tag{38}$$

$$N_{CF,t+1} = (e1'\lambda + e1'\lambda)u_{t+1} \tag{39}$$

Above, $e1$ is a vector with the first element equal to unity and the remaining elements equal to zero. The VAR shocks are mapped to news by λ, defined as $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$, and $e1'\lambda$ captures the long-run significance of each individual VAR shock to discount-rate expectations. The greater the absolute value of a variable's coefficient in the return prediction equation (the top row of Γ), the greater the weight the variable receives in the discount-rate-news formula. More persistent variables should also receive more weight, which is captured by the term $(I - \rho\Gamma)^{-1}$.

The aggregate-VAR state variables are defined as follows. First, the excess log return on the market (reM) is the difference between the annual log return on the CRSP value-weighted stock index (rM) and the annual log risk-free rate, constructed by CRSP as the return from rolling over Treasury bills with approximately three months to maturity. We take the excess return series from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html). The term yield spread (TY) is provided by Global Financial Data and is computed as the yield difference between ten-year constant-maturity taxable bonds and short-term taxable notes, in percentage points. Keim and Stambaugh (1986) and Campbell (1987) point out that TY predicts excess returns on longterm bonds. These papers argue that since stocks are also long-term assets, TY should also forecast excess stock returns, if the expected returns of longterm assets move together. Fama and French (1989) show that TY tracks the business cycle, so this variable may also capture cyclical variation in the equity premium.

We construct our third variable, the log smoothed price-earnings ratio (PE), as the log of the price of the S&P 500 index divided by a ten-year trailing moving average of aggregate earnings of companies in the index. Graham and Dodd (1934), Campbell and Shiller (1988b, 2003), and Shiller (2000) advocate averaging earnings over several years to avoid temporary spikes in the price-earnings ratio caused by cyclical declines in earnings. This variable must predict low stock returns over the long run if smoothed earnings growth is close to unpredictable. We are careful to construct the earnings series to avoid any forward-looking interpolation of earnings, ensuring that all components of the time t earnings-price ratio are contemporaneously observable. This is important because look-ahead bias in earnings can generate spurious predictability in stock returns while weakening the explanatory power of other variables in the VAR system, altering the properties of estimated news terms. Fourth, we compute the small-stock value spread (VS) using the data made available by Kenneth French on his Web site. The portfolios, which are constructed at the end of each June, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year ending in t - 1 divided by ME for December of t - 1. The BE/ME breakpoints are the 30th and 70th NYSE percentiles. At the end of June of year t, we construct the small-stock value spread as the difference between the log(BE/ME) of the small high-book-to-market portfolio and the log(BE/ME) of the small low-book-to-market portfolio, where BE and ME are measured at the end of December of year t - 1.

We include VS because of the evidence in Brennan, Wang, and Xia (2001), Campbell and Vuolteenaho (2004), and Eleswarapu and Reinganum (2004) that relatively high returns for small growth stocks predict low returns on the market as a whole. This variable can be motivated by the ICAPM itself. If small growth stocks have low and small value stocks have high expected returns, and this return differential is not explained by the static CAPM, the ICAPM requires that the excess return of small growth stocks over small value stocks be correlated with innovations in expected future market returns. There are other more direct stories that also suggest that the small-stock value spread should be related to market-wide discount rates. One possibility is that small growth stocks generate cash flows in the more distant future and, therefore, their prices are more sensitive to changes in discount rates, just as coupon bonds with a high duration are more sensitive to interest-ratemovements than are bonds with a low duration (Cornell 1999; Lettau and Wachter 2007). Another possibility is that small growth companies are particularly dependent on external financing and thus are sensitive to equity market and broader financial conditions (Ng, Engle, and Rothschild 1992; Perez-Quiros and Timmermann 2000). Finally, it is possible that episodes of irrational investor optimism (Shiller 2000) have a particularly powerful effect on small growth stocks.

C Direct measurement for cash flow news

I use accounting return on equity (ROE) to construct direct proxies for firm-level and market cash-flow news, and the price-earnings ratio to construct a proxy for market discount-rate news, following Campbell, polk, (2009), Cohen, Polk, and Vuolteenaho (2009).

After portfolio formation, we track the subsequent cash flow proxy (defined below) of our portfolios from year $t+1$ to $t+5$ by keeping the same firms in each portfolio while allowing their weights to drift with returns (as would be implied by a buy-and-hold investment strategy). Because we perform a new sort every year, our final annual data set is three-dimensional: the number of portfolios formed in each sort or characteristic, times the number of years we follow the portfolios, times the time dimension of our panel. Such portfolio formation methodology have been used by Fama and French (1995), Cohen, Polk, and Vuolteenaho (2003, 2009), and Campbell, Polk, and Vuolteenaho (2010), among others..

Specifically, after we sort the sample firms into ten portfolios for each anomaly, we compute the cash-flow beta (β_k^{CF}) for each portfolio k as the slope coefficient of a regression of portfolio's cash-flow measure on the corresponding market portfolio's cash-flow,

$$CF_{k,t} = \alpha_k^{CF} + \beta_k^{CF} CF_{M,t} + \varepsilon_{k,t}, \tag{40}$$

where $CF_{k,t}$ and $CF_{M,t}$ represent the cash-flow proxies for portfolio k and the market portfolio (sorted in year t), respectively. To asses the statistical significance of the beta estimates, we use Newey-West t-ratios (Newey and West, 1987), computed with N lags, where N denotes the horizon used in the construction of the cash-flow proxy (five years).

Following Cohen, Polk, and Vuolteenaho (2009) and Campbell, Polk, and Vuolteenaho (2010), we estimate direct measures of cash-flow news, rather than using indirect cash-flow measures implied by a first-order vector autoregression (VAR). [7] We use two main measures of cash-flow news. The first measure is similar to those employed by Ball and Brown (1969) and Beaver, Kettler, and Scholes (1970):

$$CF^1_{k,t} \equiv \sum_{j=1}^{N} \rho^{j-1} R^{CF}_{k,t,t+j} \quad \text{where} \quad R^{CF}_{k,t,t+j} = \sum_{i \in k} w_{i,t,t} \frac{X_{i,t,t+j}}{ME_{i,t,t+j-1}}. \tag{41}$$

In the formula above, the first subscript (k or i) represents respectively a portfolio or a firm; the second subscript t indicates the year when the portfolio is sorted; and the third subscript $t+j$ indicates the year when the variable is measured. In this definition, the cash-flow for portfolio k formed at time t ($CF_{k,t}$) is defined as the sum of discounted future return on equity ($R^{CF}_{k,t,t+j}$). ρ is a discount factor, linked to the average log dividend-to-price, which we set to 0.975, as in Cohen, Polk, and Vuolteenaho (2009). The portfolio is tracked for N years after the formation. We set $N = 5$ in our main estimation, but also present the results for $N = 1$ in our sensitivity analysis section. Using $N = 5$ avoids the short-term noise and volatility in earnings, which affects negatively the efficiency of the regression estimates. On the other hand, unlike Cohen, Polk, and Vuolteenaho (2009), we do not consider horizons longer than five years. The reason hinges on our relatively short sample and the fact that using longer horizons would reduce significantly the number of truly independent observations leading to statistical-inference problems in the regression above.[8]

The second equality further defines the cash-flow return on equity at portfolio level. For simplicity, we drop the first and second subscript in the text discussion that follows. We first compute for each firm the return on equity as the ratio of clean surplus earnings X_t for the fiscal year end-

[7] Campbell (1991), Campbell and Ammer (1993), Campbell and Vuolteenaho (2004), Bernanke and Kut- tner (2005), Maio (2013a), among many others, follow the VAR approach to estimate cash-flow news at the aggregate level. Under this approach, cash-flow news is the residual component of the stock return decomposition. Vuolteenaho (2002), Hecht and Vuolteenaho (2006), Campbell, Polk, and Vuolteenaho (2010), and Maio (2014) employ the same approach to estimate cash-flow news at the stock or portfolio level. On the other, Chen and Zhao (2009), Maio (2014), and Maio and Philip (2015) employ an alternative VAR-based identification in which cash-flow news is estimated directly within the VAR setup, rather than backed-up as the residual from the return decomposition.

[8] This stems from the fact that both variables in the regression contain overlapped terms, which is incorporated in the regression residuals, and as a consequence, the usual t-ratios tend to over-reject the null hypothesis of zero slopes. See Valkanov (2003), Torous, Valkanov, and Yan (2004), Boudoukh, Richardson, and Whitelaw (2008), and Hjalmarsson (2011) for a discussion in the context of predictive long-horizon regressions.

ing in calendar year t to the market value of equity at the end of December of year $t-1$, where $X_t = BE_t - BE_{t-1} + D_t^{gross}$, and D_t^{gross} denotes gross dividends computed from the difference between CRSP total stock returns and returns excluding dividends. This firm-level return on equity $(X_t/ME_t - 1)$ is winsorized at the 1% level. Then we take a weighted average of the return on equity within the portfolio k. We employ both the equal-weighting and value-weighting schemes for our empirical tests. As indicated by the third subscript of $w_{i,t,t}$, the weight assigned for each firm is determined at time t even though the clean surplus earnings and market equity take the values at time $t+j$ and $t+j-1$, respectively. This is because the same portfolio is tracked for N years after the formation, as discussed previously.

D Direct measurement for discount rate news

Again, I follow Cohen, Polk, and Vuolteenaho (2009) to use annual increments in the market's log P/E ratio, $ln(P/E)_M$. This reflects the findings of Campbell and Shiller (1988a, 1988b), Campbell (1991), and others, that discount-rate news dominates cash-flow news in aggregate returns and price volatility. The resulting news variable is

$$-DR_{M,DR,t+1} = \sum_{k=1}^{K} [\rho^{k-1} \Delta_{t+k} R_{k,t,t+j}^{DR}] \quad \text{where} \quad R_{k,t,t+j}^{DR} = \sum_{i \in k} w_{i,t,t} \ln(P/E). \tag{42}$$

Then I compute the discount rate beta (β_k^{DR}) for each portfolio k as the slope coefficient of a regression of portfolio's cash-flow measure on the corresponding market portfolio's cash-flow,

$$DR_{k,t} = \alpha_k^{DR} + \beta_k^{DR} DR_{M,t} + \varepsilon_{k,t}, \tag{43}$$

where $DR_{k,t}$ and $DR_{M,t}$ represent the discount rate proxies for portfolio k and the market portfolio (sorted in year t), respectively. To asses the statistical significance of the beta estimates, we use Newey-West t-ratios (Newey and West, 1987), computed with N lags, where N denotes the horizon used in the construction of the cash-flow proxy (five years).

To proxy for short run news, I use leading one year of accounting ROE and PE ratios; to proxy for long run news, I use $k = 2$ up to 5 years to emphasize longer-term trends that correspond more closely to the revisions in infinite-horizon expectations that are relevant for stock prices.

E Derivation of an ICAPM that features cash flow and discount rate shocks

This section derive a two factor model similar to Campbell and Vuolteenaho (2004), but relax the assumption that elasticity of intertemporal substitution equals to one.

Budget constraint:

$$W_{t+1} = (W_t - C_t)R^{\alpha}_{m,t+1} \tag{44}$$

To obtain the linearized budget constraint:

$$\Rightarrow \frac{W_{t+1}}{W_t} = (1 - \frac{C_t}{W_t})R^{\alpha}_{m,t+1} \tag{45}$$

$$\Rightarrow \Delta w_{t+1} = \alpha r_{m,t+1} + \log(1 - \exp(c_t - w_t)) \tag{46}$$

$$\Rightarrow \Delta w_{t+1} = \alpha r_{m,t+1} + \kappa + (1 - \frac{1}{\rho})(c_t - w_t) \tag{47}$$

Using the trivial identity:

$$\Delta w_{t+1} = \Delta c_{t+1} + (c_t - w_t) - (c_{t+1} - w_{t+1}) \tag{48}$$

Combine equation 47 and 48:

$$\Rightarrow \alpha r_{m,t+1} + \kappa + (1 - \frac{1}{\rho})(c_t - w_t) = \Delta c_{t+1} + (c_t - w_t) - (c_{t+1} - w_{t+1}) \tag{49}$$

$$\Rightarrow \alpha r_{m,t+1} - \Delta c_{t+1} + \kappa - \frac{1}{\rho}(c_t - w_t) = -(c_{t+1} - w_{t+1}) \tag{50}$$

$$\Rightarrow c_t - w_t = \rho(c_{t+1} - w_{t+1}) + \rho\alpha r_{m,t+1} - \rho\Delta c_{t+1} + \rho\kappa \tag{51}$$

$$\Rightarrow c_t - w_t = \sum_{j=1}^{\infty} \rho^j [\alpha r_{m,t+j} - \Delta c_{t+j}] + \frac{\rho\kappa}{1-\rho} \tag{52}$$

$$\Rightarrow c_t - w_t = E_t \sum_{j=1}^{\infty} \rho^j [\alpha r_{m,t+j} - \Delta c_{t+j}] + \frac{\rho\kappa}{1-\rho} \tag{53}$$

Substitute equation 53 into 49

$$\alpha r_{m,t+1} - \Delta c_{t+1} + \kappa - \frac{1}{\rho}[E_t \sum_{j=1}^{\infty} \rho^j [\alpha r_{m,t+j} - \Delta c_{t+j}] + \frac{\rho\kappa}{1-\rho}] \tag{54}$$

$$= -[E_{t+1} \sum_{j=1}^{\infty} \rho^j [\alpha r_{m,t+1+j} - \Delta c_{t+1+j}] + \frac{\rho\kappa}{1-\rho}] \tag{55}$$

$$\alpha r_{m,t+1} - \Delta c_{t+1} + \kappa = -E_{t+1} \sum_{j=1}^{\infty} \rho^j [\alpha r_{m,t+1+j} - \Delta c_{t+1+j}] - \frac{\rho\kappa}{1-\rho} \tag{56}$$

$$+ E_t \sum_{j=1}^{\infty} \rho^{j-1} [\alpha r_{m,t+j} - \Delta c_{t+j}] + \frac{\kappa}{1-\rho} \tag{57}$$

$$-\alpha r_{m,t+1} + \Delta c_{t+1} - \kappa - \frac{\rho\kappa}{1-\rho} + \frac{\kappa}{1-\rho} = E_{t+1} \sum_{j=1}^{\infty} \rho^j [\alpha r_{m,t+1+j} - \Delta c_{t+1+j}] \tag{58}$$

$$- E_t \sum_{j=0}^{\infty} \rho^j [\alpha r_{m,t+1+j} - \Delta c_{t+1+j}] \tag{59}$$

$$-\alpha r_{m,t+1} + \Delta c_{t+1} = E_{t+1} \sum_{j=1}^{\infty} \rho^j [\alpha r_{m,t+1+j} - \Delta c_{t+1+j}] - E_t \sum_{j=0}^{\infty} \rho^j [\alpha r_{m,t+1+j} - \Delta c_{t+1+j}] \tag{60}$$

$$(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j [\alpha r_{m,t+1+j} - \Delta c_{t+1+j}] = 0 \tag{61}$$

$$(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j [\alpha r_{m,t+1+j}] - (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta c_{t+1+j}] = 0 \tag{62}$$

$$(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j [\alpha r_{m,t+1+j}] = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta c_{t+1+j}] + \Delta c_{t+1} - E_t \Delta c_{t+1} \tag{63}$$

$$c_{t+1} - E_t c_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j[\alpha r_{m,t+1+j}] - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j \Delta c_{t+1+j}] \tag{64}$$

From the preference, the relation between consumption growth and market return:

$$E_t \Delta c_{t+1} = \mu_m + \sigma E_t r_{m,t+1} \tag{65}$$

Substitute equation 65 to 64:

$$c_{t+1} - E_t c_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j[\alpha r_{m,t+1+j}] \tag{66}$$

$$- E_{t+1}\sum_{j=1}^{\infty}\rho^j[\mu_m + \sigma r_{m,t+1}] + E_t\sum_{j=1}^{\infty}\rho^j[\mu_m + \sigma r_{m,t+1}] \tag{67}$$

$$c_{t+1} - E_t c_{t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j[\alpha r_{m,t+1+j}] - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j[\sigma r_{m,t+1+j}] \tag{68}$$

$$c_{t+1} - E_t c_{t+1} = \alpha(E_{t+1} - E_t) r_{m,t+1} + \tag{69}$$

$$\alpha(E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j r_{m,t+1+j} - \sigma(E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{m,t+1+j} \tag{70}$$

$$c_{t+1} - E_t c_{t+1} = \alpha(r_{m,t+1} - E_{t+1} r_{m,t+1}) + (\alpha - \sigma)(E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{m,t+1+j} \tag{71}$$

Covariance with consumption growth:

$$V_{ic} = \alpha V_{im} + (\sigma - \alpha)(-N_{i,t+1}^{DR}) \tag{72}$$

From preference:

$$E_t r_{i,t+1} - r_{f,t+1} = -\frac{V_i i}{2} + \theta\frac{V_{ic}}{\sigma} + (1 - \theta) V_{im} \tag{73}$$

Substitute equation 72 to 73

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_i i}{2} = \frac{\theta}{\sigma}[\alpha V_{im} + (\sigma - \alpha)(-N^{DR}_{i,t+1})] + (1-\theta)V_{im} \tag{74}$$

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_i i}{2} = (\frac{\theta}{\sigma}\alpha + 1 - \theta)V_{im} + \frac{\theta}{\sigma}(\sigma - \alpha)(-N^{DR}_{i,t+1}) \tag{75}$$

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_i i}{2} = (\frac{\theta}{\sigma}\alpha + 1 - \theta)COV_t(r_{i,t+1}, r_{m,t+1} - E_t r_{m,t+1}) \tag{76}$$

$$+ \frac{\theta}{\sigma}(\sigma - \alpha)COV_t(r_{i,t+1}, -N^{DR}_{i,t+1}) \tag{77}$$

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_i i}{2} = (\frac{\theta}{\sigma}\alpha + 1 - \theta)COV_t(r_{i,t+1}, N^{CF}_{i,t+1} - N^{DR}_{i,t+1}) \tag{78}$$

$$+ \frac{\theta}{\sigma}(\sigma - \alpha)COV_t(r_{i,t+1}, -N^{DR}_{i,t+1}) \tag{79}$$

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_i i}{2} = (\frac{\theta}{\sigma}\alpha + 1 - \theta)\sigma^2_m \beta^{CF} + (\frac{\theta}{\sigma}(\sigma - \alpha) + \frac{\theta}{\sigma}\alpha + 1 - \theta)\sigma^2_m \beta^{DR} \tag{80}$$

$$E_t r_{i,t+1} - r_{f,t+1} + \frac{V_{ii}}{2} = (\frac{\theta}{\sigma}\alpha + 1 - \theta)\sigma^2_m \beta^{CF} + \sigma^2_m \beta^{DR} \tag{81}$$

A Tables

Table 1: Summary statistics for portfolios sorted by orthogonalized duration

This table reports the monthly value-weighted average returns(R^e), the equal-weighted average book-to-market ratio(BM), and interest rate sensitivity (β^I) for the decile portfolios formed on the unorthogonalized duration (DUR) in panel A, and orthogonalized duration (DUR^r) in panel B. The last column $Long - Short$ reports the spreads for each variable. The t-statistics are reported in parentheses. The sample for the portfolio returns is monthly from July 1968 to December 2015. The interest rate sensitivity is computed from an event study by regressing the 5 days average returns of these portfolios on the interest rate surprise after the FOMC meeting. The event date is the announcement date of the FOMC meeting on day t, while the reaction date is from $t + 1$ to $t + 6$. The interest rate surprise is estimated with the method as in Bernanke and Kuttner (2005)

Panel A: unorthogonalized duration											
	Short DUR	2	3	4	5	6	7	8	9	Long DUR	Long−Short
R^e	0.7216	0.8124	0.7607	0.6471	0.7082	0.4387	0.5621	0.5641	0.4999	0.3515	−.3701
	(3.13***)	(4.30***)	(4.23***)	(3.72***)	(3.78***)	(2.48**)	(3.04***)	(3.07***)	(2.58**)	(1.51)	(−2.14**)
BM	1.60	1.21	1.09	0.95	0.79	0.73	0.64	0.58	0.57	0.77	−0.98
	(21.35***)	(18.51***)	(12.17***)	(16.67***)	(22.41***)	(17.87***)	(18.81***)	(15.73***)	(8.18***)	(8.60***)	(−14.84***)
β^I	0.14	0.27	0.19	0.23	−0.00	0.27	0.04	0.23	−0.23	−0.56	−0.70
	(0.53)	(1.26)	(1.00)	(1.24)	(−0.02)	(1.52)	(0.32)	(1.78*)	(−1.54)	(−2.53**)	(−2.20**)

Table 1: (continued)

Panel B: orthogonalized duration											
	Short DUR^r	2	3	4	5	6	7	8	9	Long DUR^r	Long−Short
R^e	0.6923	0.8387	0.6459	0.6579	0.5959	0.5863	0.4068	0.4363	0.3397	0.0782	−.6141
	(2.96***)	(4.21***)	(3.49***)	(3.64***)	(3.30***)	(3.25***)	(2.22**)	(2.33**)	(1.53)	(0.31)	(−4.11***)
BM	1.02	0.85	0.77	0.74	0.70	0.68	0.68	0.71	0.78	1.03	0.00
	(19.22***)	(18.90***)	(19.75***)	(21.15***)	(20.34***)	(22.54***)	(22.45***)	(26.80***)	(27.06***)	(27.07***)	(0.16)
β^I	−0.03	0.29	0.15	0.08	−0.01	−0.24	−0.56	−0.29	−0.48	−0.98	−0.95
	(−0.11)	(1.59)	(1.09)	(0.57)	(−0.08)	(−1.57)	(−3.42***)	(−1.80*)	(−2.17**)	(−3.29***)	(−2.92***)

Table 2: Univariate Analysis

This table reports the equal-weighted the abnormal investment 3 years into the future (ACI), cash flow beta (β^{CF}) and the discount rate beta (β^{DR}) for ten portfolios formed on the orthogonalized duration (DUR). Following Titman et al. (2004), the abnormal investment at time t is defined as the capital expenditure at time $t-1$ divided by the three years average of capital expenditure from $t-2$ to $t-4$ minus one. The cash flow beta is estimated as the coefficient from a regression of portfolio level cash flow on the market level cash flow. The discount beta is estimated as the coefficient from a regression of portfolio level discount rate on the market level discount rate. The sample covers annual firm level data from 1968 to 2015. The last column $Long - Short$ reports the spreads for each variable. The t-statistics are reported in parentheses.

Stat	Low	2	3	4	5	6	7	8	9	High	High−Low
					Panel A: orthogonalized duration						
ACI	0.12	0.08	0.07	0.05	0.04	0.04	0.04	0.04	0.03	0.06	−0.06
	(5.95***)	(4.69***)	(4.40***)	(3.47***)	(3.35***)	(3.47***)	(2.14**)	(2.07**)	(1.34)	(3.08***)	(−3.62***)
β^{CF}	1.50	1.36	1.25	1.33	1.18	1.19	0.94	0.88	0.70	0.97	−0.53
	(11.75***)	(11.35***)	(11.44***)	(19.92***)	(16.25***)	(22.98***)	(11.56***)	(12.05***)	(11.77***)	(8.36***)	(−2.81***)
β^{DR}	0.86	0.93	1.09	0.90	0.93	0.84	0.97	0.98	0.93	0.73	−0.13
	(7.38***)	(9.29***)	(12.21***)	(13.79***)	(10.14***)	(14.49***)	(11.27***)	(15.74***)	(14.24***)	(7.47***)	(−0.82)

Table 3: Double-sorts by orthogonalized duration and book-to-market ratio

Panel A presents value weighted average portfolio excess returns(R^e) and the corresponding t-statistics for a 5x5 portfolios sorted by book-to-market ratio (BM) and orthogonalized duration (DUR^r). Panel B presents the cash flow betas (β^{CF}) and the corresponding t-statistics for the same 5x5 portfolios. Panel C presents the discount rate betas (β^{DR}) and the corresponding t-statistics for the same 5x5 portfolios. The cash flow beta is estimated as the coefficient from a regression of portfolio level cash flow on the market level cash flow. The discount beta is estimated as the coefficient from a regression of portfolio level discount rate on the market level discount rate. The sample for the portfolio returns is monthly from July 1968 to December 2015, while the sample for the remaining variables are annual from 1968 to 2015. The last rows for all the three panels reports the spreads between high and low BM portfolios. The last columns for all the three panels reports the spreads between long and short DUR^r portfolios. The t-statistics are reported in parentheses.

BM quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel A: return												
	Mean						t-value					
Low BM	0.8839	0.6598	0.5913	0.2964	−.0299	−.9138	(3.36***)	(3.11***)	(3.00***)	(1.39)	(−0.11)	(−5.30***)
BM 2	0.9310	0.6632	0.6006	0.3861	0.1173	−.8260	(4.08***)	(3.48***)	(3.14***)	(1.90*)	(0.47)	(−4.75***)
BM 3	0.7339	0.5569	0.6327	0.4495	0.4689	−.2650	(3.41***)	(2.88***)	(3.29***)	(2.24**)	(1.95*)	(−1.68*)
BM 4	0.7396	0.8063	0.6270	0.6270	0.4029	−.3367	(3.58***)	(4.31***)	(3.49***)	(3.19***)	(1.80*)	(−2.11**)
High BM	0.6803	0.8977	1.1332	1.0071	0.8517	0.1715	(3.00***)	(4.57***)	(5.22***)	(4.28***)	(3.18***)	(1.00)
High−Low	−.2036	0.2379	0.5419	0.7242	0.8816	1.0853	(−1.05)	(1.29)	(2.79***)	(3.38***)	(4.18***)	(4.99***)

Table 3: (continued)

BM quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel B: CF beta												
	Estimate						t-value					
Low BM	1.50	0.98	0.79	0.50	0.35	−1.15	(8.26***)	(14.79***)	(13.99***)	(7.45***)	(3.86***)	(−5.55***)
BM 2	1.56	1.15	0.97	0.99	0.95	−0.61	(10.46***)	(13.98***)	(11.60***)	(10.60***)	(8.30***)	(−4.29***)
BM 3	1.72	1.37	1.31	1.27	1.43	−0.29	(13.65***)	(8.74***)	(8.28***)	(8.22***)	(9.63***)	(−1.54)
BM 4	1.19	1.24	1.56	1.47	1.86	0.67	(6.74***)	(8.94***)	(10.66***)	(10.31***)	(11.82***)	(2.58**)
High BM	1.33	1.56	1.32	1.79	1.90	0.57	(6.94***)	(9.01***)	(7.15***)	(7.48***)	(7.60***)	(1.75*)
High−Low	−0.17	0.58	0.53	1.29	1.55	1.72	(−0.68)	(3.20***)	(2.55**)	(4.91***)	(5.64***)	(4.12***)
Panel C: DR beta												
	Estimate						t-value					
Low BM	0.54	0.67	0.75	0.80	0.77	0.22	(4.38***)	(9.69***)	(12.21***)	(8.23***)	(11.70***)	(1.82*)
BM 2	0.71	0.94	0.76	0.75	0.69	−0.02	(7.39***)	(14.46***)	(9.63***)	(6.12***)	(6.99***)	(−0.19)
BM 3	0.85	0.88	0.94	0.89	0.76	−0.09	(11.12***)	(8.61***)	(10.66***)	(10.36***)	(7.22***)	(−0.70)
BM 4	0.80	1.03	0.77	0.85	0.94	0.14	(5.53***)	(9.00***)	(8.83***)	(6.56***)	(8.97***)	(0.86)
High BM	0.95	0.83	1.03	0.89	0.65	−0.29	(6.96***)	(7.00***)	(6.51***)	(6.80***)	(4.24***)	(−1.34)
High−Low	0.41	0.17	0.28	0.09	−0.11	−0.52	(2.14**)	(1.19)	(1.58)	(0.54)	(−0.75)	(−2.13**)

Table 4: Portfolio characteristics for double-sorted portfolios

This table shows the equal weighted average book-to-market ratio (BM) and the corresponding t-statistics for the portfolios double sorted by book-to-market ratio(BM) and orthogonalized duration (DUR^r). The sample is annual from 1968 to 2015.

BM quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
	Mean						t-value					
Low BM	0.23	0.24	0.23	0.23	0.23	−0.01	(17.62***)	(19.14***)	(20.15***)	(20.70***)	(19.73***)	(−2.49**)
BM 2	0.48	0.47	0.47	0.47	0.48	−0.00	(20.20***)	(20.57***)	(20.59***)	(20.50***)	(20.27***)	(−1.01)
BM 3	0.68	0.68	0.68	0.68	0.68	−0.00	(20.95***)	(21.03***)	(21.07***)	(21.12***)	(21.23***)	(−0.12)
BM 4	0.94	0.93	0.93	0.93	0.94	−0.00	(22.92***)	(22.56***)	(22.86***)	(23.01***)	(22.70***)	(−0.25)
High BM	1.75	1.63	1.63	1.65	1.83	0.09	(26.53***)	(25.49***)	(24.45***)	(24.54***)	(28.37***)	(6.93***)
High−Low	1.51	1.39	1.39	1.44	1.61	0.10	(26.35***)	(25.44***)	(23.26***)	(24.39***)	(27.16***)	(7.39***)

Table 5: Double-sorts by orthogonalized duration and gross-profit-to-asset ratio

Panel A presents value weighted average portfolio excess returns(R^e) and the corresponding t-statistics for a 5x5 portfolios sorted by gross-profit-to-asset ratio (GPA) and orthogonalized duration (DUR^r). Panel B presents the cash flow betas (β^{CF}) and the corresponding t-statistics for the same 5x5 portfolios. Panel C presents the discount rate betas (β^{DR}) and the corresponding t-statistics for the same 5x5 portfolios. The cash flow beta is estimated as the coefficient from a regression of portfolio level cash flow on the market level cash flow. The discount beta is estimated as the coefficient from a regression of portfolio level discount rate on the market level discount rate. The sample for the portfolio returns is monthly from July 1968 to December 2015, while the sample for the remaining variables are annual from 1968 to 2015. The last rows for all the three panels reports the spreads between high and low GPA portfolios. The last columns for all the three panels reports the spreads between long and short DUR^r portfolios. The t-statistics are reported in parentheses.

GPA quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel A: return												
	Mean						t-value					
Low GPA	0.4375	0.5514	0.3953	0.4373	0.2014	−.2416	(1.97**)	(2.94***)	(2.18**)	(2.34**)	(0.79)	(−1.37)
GPA 2	0.6370	0.5092	0.6565	0.3353	0.0748	−.5622	(2.86***)	(2.54**)	(3.27***)	(1.62)	(0.31)	(−3.59***)
GPA 3	0.8321	0.7209	0.4193	0.5601	0.2838	−.5484	(3.60***)	(3.57***)	(2.05**)	(2.81***)	(1.15)	(−3.20***)
GPA 4	0.9270	0.6049	0.6684	0.3923	0.3476	−.5794	(3.93***)	(2.86***)	(3.23***)	(1.82*)	(1.25)	(−3.11***)
High GPA	1.1820	0.9034	0.7357	0.3480	0.3400	−.8420	(4.82***)	(4.50***)	(3.93***)	(1.67*)	(1.32)	(−4.38***)
High−Low	0.7555	0.3520	0.3404	−.0832	0.1386	−.6198	(4.22***)	(2.43**)	(2.27**)	(−0.48)	(0.79)	(−2.65***)

Table 5: (continued)

GPA quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel B: CF beta												
	Estimate						t-value					
Low GPA	1.75	1.60	2.05	2.00	2.21	0.46	(8.04***)	(8.45***)	(17.24***)	(15.99***)	(12.59***)	(1.54)
GPA 2	1.12	1.13	0.97	0.83	0.86	−0.27	(6.72***)	(8.24***)	(7.92***)	(5.98***)	(7.47***)	(−1.34)
GPA 3	1.28	1.13	0.94	1.03	0.88	−0.40	(9.80***)	(10.15***)	(11.38***)	(16.46***)	(7.73***)	(−2.35**)
GPA 4	1.58	1.20	1.02	0.75	0.52	−1.06	(10.73***)	(15.53***)	(17.34***)	(10.14***)	(4.76***)	(−6.61***)
High GPA	1.51	1.15	0.88	0.63	0.51	−1.00	(8.87***)	(16.88***)	(11.18***)	(7.91***)	(7.04***)	(−4.86***)
High−Low	−0.24	−0.45	−1.17	−1.38	−1.70	−1.46	(−0.86)	(−2.12**)	(−7.44***)	(−8.77***)	(−7.92***)	(−3.64***)
Panel C: DR beta												
	Estimate						t-value					
Low GPA	1.01	1.23	1.27	1.05	0.73	−0.27	(8.58***)	(10.49***)	(10.75***)	(9.65***)	(5.51***)	(−1.27)
GPA 2	0.96	0.94	0.72	0.90	0.75	−0.21	(6.19***)	(10.21***)	(7.10***)	(10.93***)	(8.01***)	(−1.02)
GPA 3	0.86	0.88	0.87	0.88	0.87	0.01	(9.00***)	(10.00***)	(11.85***)	(10.93***)	(8.28***)	(0.05)
GPA 4	0.52	0.85	0.70	0.78	0.77	0.25	(4.88***)	(8.00***)	(8.90***)	(8.01***)	(8.66***)	(1.65)
High GPA	0.60	0.83	0.88	0.94	0.82	0.22	(5.40***)	(9.23***)	(9.64***)	(10.30***)	(10.16***)	(1.71*)
High−Low	−0.41	−0.40	−0.39	−0.11	0.09	0.50	(−3.18***)	(−3.18***)	(−2.84***)	(−0.77)	(0.69)	(2.42**)

Table 6: Double-sorts by orthogonalized duration and sales growth

Panel A presents value weighted average portfolio excess returns(R^e) and the corresponding t-statistics for a 5x5 portfolios sorted by sales growth (SG) and orthogonalized duration (DUR^r). Panel B presents the cash flow betas (β^{CF}) and the corresponding t-statistics for the same 5x5 portfolios. Panel C presents the discount rate betas (β^{DR}) and the corresponding t-statistics for the same 5x5 portfolios. The cash flow beta is estimated as the coefficient from a regression of portfolio level cash flow on the market level cash flow. The discount beta is estimated as the coefficient from a regression of portfolio level discount rate on the market level discount rate. The sample for the portfolio returns is monthly from July 1968 to December 2015, while the sample for the remaining variables are annual from 1968 to 2015. The last rows for all the three panels reports the spreads between high and low SG portfolios. The last columns for all the three panels reports the spreads between long and short DUR^r portfolios. The t-statistics are reported in parentheses.

SG quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel A: return												
	Mean						t-value					
Low SG	0.8340	0.9735	0.5056	0.6437	0.5647	−.2692	(3.79***)	(5.04***)	(2.68***)	(3.33***)	(2.39**)	(−1.62)
SG 2	0.8755	0.5927	0.6235	0.5578	0.2611	−.6144	(4.13***)	(3.23***)	(3.33***)	(3.12***)	(1.13)	(−3.58***)
SG 3	0.6881	0.6473	0.5026	0.5157	0.3849	−.3028	(3.18***)	(3.67***)	(2.81***)	(2.83***)	(1.69*)	(−1.69*)
SG 4	0.6363	0.7738	0.5508	0.4179	0.2975	−.3388	(2.89***)	(3.68***)	(2.99***)	(2.12**)	(1.26)	(−1.82*)
High SG	0.9164	0.5218	0.7907	0.3974	0.1264	−.7900	(3.43***)	(2.37**)	(3.60***)	(1.79*)	(0.48)	(−4.35***)
High−Low	0.0825	−.4517	0.2850	−.2463	−.4383	−.5208	(0.45)	(−2.97***)	(1.65)	(−1.39)	(−2.18**)	(−2.22**)

Table 6: (continued)

SG quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel B: CF beta												
	Estimate						t-value					
Low SG	1.45	1.09	1.18	1.21	1.04	−0.40	(9.40***)	(8.66***)	(8.74***)	(7.71***)	(5.31***)	(−1.50)
SG 2	1.31	1.14	1.13	0.97	0.84	−0.47	(8.82***)	(12.35***)	(14.77***)	(8.91***)	(8.46***)	(−2.62**)
SG 3	1.50	1.34	1.17	0.80	0.73	−0.76	(8.19***)	(12.99***)	(12.64***)	(6.62***)	(5.15***)	(−3.73***)
SG 4	1.14	1.45	1.26	0.94	0.57	−0.57	(8.02***)	(9.61***)	(17.01***)	(11.56***)	(4.67***)	(−2.76***)
High SG	1.58	1.32	1.23	1.05	0.88	−0.70	(7.67***)	(11.61***)	(11.63***)	(10.11***)	(7.83***)	(−2.69**)
High−Low	0.13	0.24	0.05	−0.16	−0.16	−0.29	(0.52)	(1.53)	(0.28)	(−0.80)	(−0.68)	(−0.80)
Panel C: DR beta												
	Estimate						t-value					
Low SG	0.71	0.85	0.81	1.06	0.63	−0.07	(8.94***)	(6.84***)	(8.09***)	(8.36***)	(5.61***)	(−0.52)
SG 2	0.86	0.91	0.87	1.06	0.87	0.01	(7.10***)	(10.27***)	(11.29***)	(10.02***)	(6.60***)	(0.06)
SG 3	0.86	1.05	0.97	0.96	0.59	−0.27	(7.25***)	(13.33***)	(11.75***)	(10.27***)	(8.08***)	(−1.93*)
SG 4	0.91	0.99	0.91	0.93	0.97	0.06	(5.40***)	(10.69***)	(10.66***)	(14.15***)	(8.07***)	(0.27)
High SG	0.69	0.69	0.56	0.83	0.81	0.13	(6.24***)	(5.96***)	(7.82***)	(7.48***)	(11.87***)	(0.88)
High−Low	−0.02	−0.17	−0.25	−0.23	0.18	0.20	(−0.14)	(−1.24)	(−2.03**)	(−1.26)	(1.42)	(1.06)

Table 7: Double-sorts by orthogonalized duration and operating leverage

Panel A presents value weighted average portfolio excess returns(R^e) and the corresponding t-statistics for a 5x5 portfolios sorted by operating leverage (OL) and orthogonalized duration (DUR^r). Panel B presents the cash flow betas (β^{CF}) and the corresponding t-statistics for the same 5x5 portfolios. Panel C presents the discount rate betas (β^{DR}) and the corresponding t-statistics for the same 5x5 portfolios. The cash flow beta is estimated as the coefficient from a regression of portfolio level cash flow on the market level cash flow. The discount beta is estimated as the coefficient from a regression of portfolio level discount rate on the market level discount rate. The sample for the portfolio returns is monthly from July 1968 to December 2015, while the sample for the remaining variables are annual from 1968 to 2015. The last rows for all the three panels reports the spreads between high and low OL portfolios. The last columns for all the three panels reports the spreads between long and short DUR^r portfolios. The t-statistics are reported in parentheses.

OL quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel A: return												
	Mean						t-value					
Low OL	0.6680	0.5758	0.6206	0.3155	−.0733	−.7413	(2.73***)	(2.72***)	(2.71***)	(1.58)	(−0.28)	(−3.88***)
OL 2	0.7273	0.7705	0.6526	0.3681	0.1986	−.5287	(2.93***)	(3.80***)	(3.30***)	(1.72*)	(0.72)	(−2.91***)
OL 2	0.8844	0.7220	0.5980	0.6311	0.3810	−.5034	(3.60***)	(3.32***)	(2.89***)	(2.85***)	(1.42)	(−2.72***)
OL 2	0.8922	0.8771	0.6872	0.3511	0.4063	−.4859	(3.13***)	(3.89***)	(3.49***)	(1.60)	(1.56)	(−2.44**)
High OL	0.9340	0.9496	0.8534	0.5941	0.6006	−.3631	(3.84***)	(4.58***)	(3.80***)	(2.59***)	(2.34**)	(−2.11**)
High−Low	0.2659	0.3738	0.2328	0.2786	0.6441	0.3782	(1.37)	(2.18**)	(1.36)	(1.76*)	(3.51***)	(1.72*)

Table 7: (continued)

OL quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel B: CF beta												
	Estimate						t-value					
Low OL	1.61	1.51	1.15	1.03	0.64	−0.97	(7.28***)	(8.56***)	(11.86***)	(8.91***)	(4.23***)	(−3.92***)
OL 2	1.44	1.20	1.01	0.91	0.86	−0.58	(7.53***)	(10.91***)	(16.02***)	(11.13***)	(8.07***)	(−2.75***)
OL 3	1.21	1.29	1.00	0.70	0.58	−0.63	(6.01***)	(14.07***)	(9.50***)	(8.06***)	(3.55***)	(−2.38**)
OL 4	1.49	1.27	1.02	0.96	0.88	−0.61	(12.34***)	(13.91***)	(11.03***)	(11.94***)	(5.26***)	(−3.28***)
High OL	1.55	1.45	1.40	1.12	0.80	−0.75	(7.47***)	(12.15***)	(13.75***)	(12.36***)	(7.23***)	(−3.53***)
High−Low	−0.06	−0.06	0.26	0.09	0.16	0.22	(−0.16)	(−0.31)	(2.04**)	(0.64)	(0.95)	(0.72)
Panel C: DR beta												
	Estimate						t-value					
Low OL	0.63	0.88	0.74	0.98	0.99	0.36	(7.06***)	(7.02***)	(7.37***)	(8.16***)	(9.75***)	(2.44**)
OL 2	1.02	1.01	0.88	0.95	0.92	−0.10	(7.75***)	(9.99***)	(7.72***)	(12.28***)	(8.51***)	(−0.64)
OL 3	0.61	0.77	0.93	1.11	0.79	0.19	(6.13***)	(6.58***)	(12.08***)	(9.86***)	(10.24***)	(1.51)
OL4	0.88	0.90	0.91	0.94	0.53	−0.35	(6.06***)	(8.13***)	(8.07***)	(6.08***)	(5.01***)	(−2.02*)
High OL	0.92	1.06	0.85	0.90	1.00	0.08	(5.15***)	(8.91***)	(8.97***)	(10.76***)	(13.15***)	(0.39)
High−Low	0.29	0.18	0.10	−0.08	0.01	−0.28	(1.63)	(1.14)	(0.74)	(−0.50)	(0.09)	(−1.68)

Table 8: Double-sorts by orthogonalized duration computed with time varying discount rate and book-to-market ratio

Panel A presents value weighted average portfolio excess returns(R^e) and the corresponding t-statistics for a 5x5 portfolios sorted by book-to-market ratio (BM) and orthogonalized duration (DUR^r) computed using time-varying discount rate. Panel B presents the cash flow betas (β^{CF}) and the corresponding t-statistics for the same 5x5 portfolios. Panel C presents the discount rate betas (β^{DR}) and the corresponding t-statistics for the same 5x5 portfolios. The cash flow beta is estimated as the coefficient from a regression of portfolio level cash flow on the market level cash flow. The discount beta is estimated as the coefficient from a regression of portfolio level discount rate on the market level discount rate. The sample for the portfolio returns is monthly from July 1968 to December 2015, while the sample for the remaining variables are annual from 1968 to 2015. The last rows for all the three panels reports the spreads between high and low GPA portfolios. The last columns for all the three panels reports the spreads between long and short DUR^r portfolios. The t-statistics are reported in parentheses.

BN quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel A: return												
	Mean						t-value					
Low BM	0.5385	0.7258	0.2120	0.4912	0.3149	−.2235	(2.59***)	(3.50***)	(0.99)	(2.18**)	(1.28)	(−1.71*)
BM 2	0.7520	0.6435	0.5517	0.3463	0.4099	−.3421	(3.68***)	(3.32***)	(2.66***)	(1.73*)	(1.88*)	(−2.55**)
BM 3	0.8261	0.6176	0.5207	0.4967	0.4546	−.3714	(3.92***)	(2.99***)	(2.68***)	(2.50**)	(2.20**)	(−2.85***)
BM 4	0.7217	0.6937	0.6078	0.5038	0.6242	−.0975	(3.14***)	(3.57***)	(3.27***)	(2.73***)	(3.00***)	(−0.64)
High BM	0.6885	0.9670	0.8442	0.8734	0.9137	0.2450	(2.80***)	(4.67***)	(4.35***)	(3.88***)	(3.62***)	(1.48)
High−Low	0.1583	0.2412	0.6322	0.3822	0.5987	0.4692	(0.84)	(1.25)	(3.48***)	(1.81*)	(2.75***)	(2.28**)

Table 8: (continued)

BN quintile	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short	Short Dur^r	Dur^r 2	Dur^r 3	Dur^r 4	Long Dur^r	Long-Short
Panel B: CF beta												
	Estimate						t-value					
Low BM	0.58	0.70	0.58	0.55	0.47	−0.10	(9.41***)	(15.97***)	(9.06***)	(8.52***)	(5.48***)	(−1.12)
BM 2	1.41	1.24	1.13	0.93	0.84	−0.57	(12.21***)	(13.32***)	(12.48***)	(10.82***)	(7.76***)	(−5.02***)
BM 3	1.73	1.66	1.38	1.16	1.42	−0.30	(13.03***)	(15.79***)	(10.93***)	(6.40***)	(10.56***)	(−2.07**)
BM 4	1.35	1.34	1.33	1.41	1.80	0.44	(7.43***)	(9.19***)	(8.89***)	(10.45***)	(12.50***)	(2.16**)
High BM	1.58	1.17	1.45	1.52	1.77	0.19	(8.92***)	(4.96***)	(7.03***)	(11.14***)	(8.20***)	(0.61)
High−Low	1.00	0.47	0.87	0.96	1.29	0.29	(5.46***)	(1.87*)	(3.88***)	(5.82***)	(5.02***)	(0.87)
Panel C: DR beta												
	Estimate						t-value					
Low BM	0.89	0.75	0.74	0.73	0.80	−0.09	(13.36***)	(12.39***)	(10.20***)	(11.09***)	(8.37***)	(−0.85)
BM 2	0.85	0.85	0.80	0.70	0.77	−0.09	(11.65***)	(14.18***)	(9.78***)	(6.38***)	(9.58***)	(−0.72)
BM 3	0.75	0.75	0.89	1.00	0.86	0.11	(9.98***)	(6.92***)	(12.15***)	(10.77***)	(10.88***)	(1.25)
BM 4	0.76	0.82	0.94	0.99	0.76	−0.00	(6.04***)	(5.16***)	(7.33***)	(9.68***)	(7.78***)	(−0.01)
High BM	0.89	1.02	0.75	0.86	0.89	0.01	(6.81***)	(7.99***)	(4.70***)	(7.11***)	(7.93***)	(0.06)
High−Low	−0.00	0.27	0.01	0.13	0.10	0.10	(−0.00)	(1.66)	(0.03)	(1.10)	(0.56)	(0.54)

Table 9: Prices of risks estimation

Panel A reports the prices of cash flow risk (λ^{CF}) and discount rate risk (λ^{DR}). The prices are estimated by regressing the returns of two sets of decile portfolios single-sorted by book-to-market ratio (BM), and orthogonalized duration (DUR^r) on their corresponding betas computed from the direct measurement approach following Campbell and Vuolteenaho (2004) The model specification is: $E[R_i] = \lambda^{CF}\beta_i^{CF} + \lambda^{DR}\beta_i^{DR}$. Panel B reports the realized and predicted return spreads for two sets of decile portfolios, namely the portfolios by sorted book-to-market ratio(BM), and the portfolios by sorted orthogonalized duration (DUR^r). The predicted return of each decile is computed from the two factors model as above, with the estimated price of risk shown in panel A. The first column indicates the variable by which I sort the portfolios. The second and third column respectively reports the realized and predicted return spread by taking the difference between the extreme portfolios. The last column computes the ratio of predicted spreads over the realized spreads.

Panel A: Price of risk

	Intercept	λ^{CF}	λ^{DR}	R^2
Estimates	−0.0018	0.0039	0.0033	0.4969
t-Value	−0.5538	3.6699	0.8767	.

Panel B: Performance of two-factor model

Return Spread	realized	predicted	fraction
DUR^r	−0.0032	−0.0022	0.6765
BM	0.0049	0.0039	0.7894

Table 10: Prices of risks estimation

The prices of cash flow risk (λ^{CF}) and discount rate risk (λ^{DR}) are estimated by regressing the returns of two sets of decile portfolios single-sorted by book-to-market ratio (BM), and orthogonalized duration (DUR^r) on their corresponding betas computed from the direct measurement approach following Campbell and Vuolteenaho (2004) The model specification is: $E[R_i] = \lambda^{CF}\beta_i^{CF} + \lambda^{DR}\beta_i^{DR}$. Panel B reports the realized and predicted return spreads for two sets of decile portfolios, namely the portfolios by sorted book-to-market ratio(BM), and the portfolios by sorted orthogonalized duration (DUR^r). The predicted return of each decile is computed from the two factors model as above, with the estimated price of risk shown in panel A. The first column indicates the variable by which I sort the portfolios. The second and third column respectively reports the realized and predicted return spread by taking the difference between the extreme portfolios. The last column computes the ratio of predicted spreads over the realized spreads.

Panel A: Price of risk

	Intercept	λ^{CF}	λ^{DR}	R^2
Estimates	−0.0009	0.0042	0.0022	0.4011
t-Value	−0.2897	3.6913	0.6002	.

Panel B: Performance of two-factor model

Return Spread	realized	predicted	fraction
Low BM	−0.0091	−0.0043	0.4741
BM 2	−0.0081	−0.0026	0.3241
BM 3	−0.0027	−0.0014	0.5323
BM 4	−0.0034	0.0031	−0.9339
High BM	0.0017	0.0017	1.0202

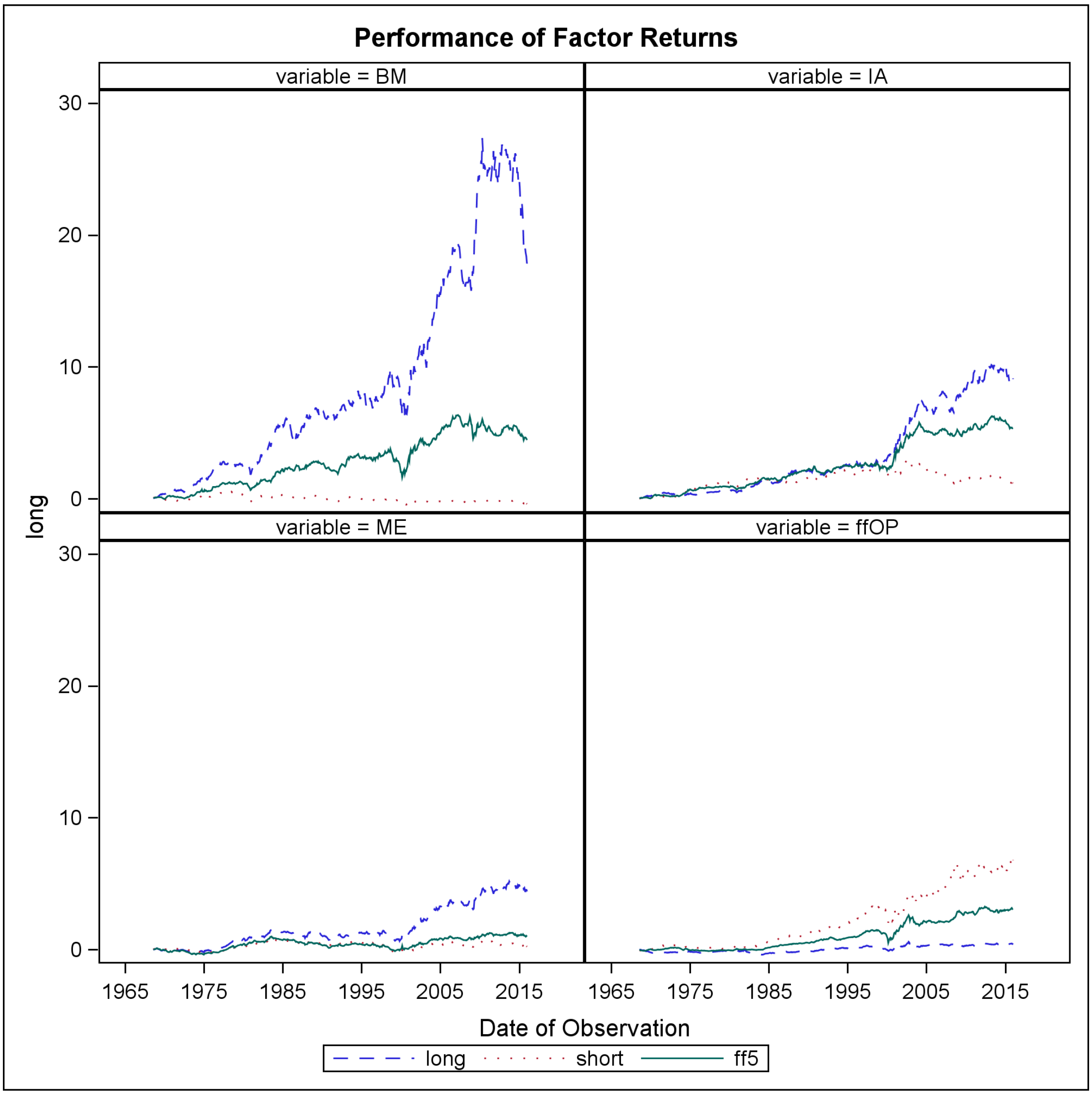

Figure 1: Close-up of a gull

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