Dividends, Earnings and Expected Return in the Context of Consumption Risk

by

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Abstract

The consumption literature of asset pricing typically considers only dividend cash flows, based on the theoretical inference that consumption must equal dividends over the long run. Where it is commonly considered that dividends are the smooth permanent component of earnings, while earnings vary with the business cycle. Motivated by Lamont's (1998) result that earnings and dividends have opposite effects on future return, we follow the empirical methodology of Boguth and Kuehn (2013) and find that dividend growth volatility and earnings growth volatility have opposite relationships to consumption volatility risk. We show that these opposing effects of dividends and earnings are components of the mechanism connecting consumption risk and investors' expected return. These results offer insight for a piece of the equity premium puzzle, namely, why stock return volatility is large compared to consumption volatility.

Preface

My supervisor, Dr. David Koslowsky, provided guidance to me for completing this thesis. I generated all the tables in my thesis and wrote the draft of the dissertation paper. Dr. Koslowsky edited my drafts and suggested revisions. In future, we are planning to turn the paper into a publication at a peer reviewed journal.

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Lists of symbols, abbreviations or other

BK: Boguth and Kuehn (2013)

μ_l^s: Expected service consumption growth in low state

μ_h^s: Expected service consumption growth in high state

σ_l^s: Expected service consumption volatilities in low state

σ_h^s: Expected service consumption volatilities in high state

μ_l^v: Expected service consumption share growth in low state

μ_h^v: Expected service consumption share growth in high state

σ_l^v: Expected service consumption share volatilities in low state

σ_h^v: Expected service consumption share volatilities in high state

p_μ^{ll}: The probability in a mean regime of low state

p_μ^{hh}: The probability in a mean regime of high state

p_σ^{ll}: The probability in an volatility regime of low state

p_σ^{hh}: The probability in an volatility regime of low state

ϱ_{sv}: Correlation

EW: Equally-weighted portfolio return

VW: Value-weighted portfolio return

LOW: Firms that have lowest rank based on risk loadings of equation 12

MED: Firms that have middle rank based on risk loadings of equation 12

HIGH: Firms that have highest rank based on risk loadings of equation 12

High-Low: Holding return from a zero portfolio that simultaneously taking a long position in the HIGH sorted portfolio and a short position in the LOW sorted portfolio

β_σ: Risk loadings on change in the second moment of consumption growth

St.Dev: Standard deviation of the value-weighted portfolio return

ME: Size of a portfolio

BM: Book-to-market ratio

MOM: Momentum

CVR: Consumption volatility risk which is defined as a value-weighted holding return from taking a long position for firms that have high risk loadings on consumption volatility and also taking a short position for firms that have low risk loadings on consumption volatility.

MKT: Market risk premium

SMB: Size risk premium

HML: Value risk premium

ER: Excess return

$\emptyset_{\mu}$: Coefficient on the first moment of consumption

$\emptyset_{\sigma}$: Coefficient on the second moment of consumption

CRSP: Center for Research in Security Prices.

PERMNO: CRSP Permanent Company Number.

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I am grateful to have Dr. David Koslowsky as my supervisor, and Dr. Arjun Bhardwaj and Dr. Mohsen Javdani in my supervisory committee. I deeply appreciate for their help in enlightening me in my research. Especially, I thank you, Dr. Koslowsky, who has given me all the tools in doing research. I would not be there without him. This thesis is a collaboration between Dr. Koslowsky and me. We thank Oliver Boguth for providing us with the Matlab programming codes to run the Multivariate Markov Model and his guidance in creating Table 2.

Chapter 1 Introduction

The consumption-based asset pricing literature that examines the link between consumption and expected return focuses on dividend growth as the intermediate cash flow variable that moves prices, with the connection between dividends and earnings receiving limited attention. For example, Lettau and Ludvigson (2005) find a positive correlation between dividend growth and expected return over the business cycle. And more recently, Boguth and Kuehn (2013) show that time varying aggregate consumption volatility leads to an expected risk premium that can be explained by cross-sectional differences in dividend cash flow loadings on consumption volatility risk. However, outside of the consumption-based literature, the empirical evidence of Lamont (1998) shows that dividends and earnings have an opposite relationship to future return, with dividend yield positively related and earnings yield negatively related. Lamont (1998) attributes this opposite relationship to the view that earnings move with the economic cycle, while dividends represent the permanent component of cash flow within the economic cycle. The main contribution of this paper is to show that the opposite relation of dividends and earnings to expected return observed by Lamont (1998) may be explained by opposite loadings on consumption volatility risk, such that the conjoined effect of dividend and earnings cash flows is the mechanism by which consumption risk transmits to expected return.

The different characteristics of dividend growth and earnings growth during the consumption cycle are important because they have a significant impact on expected returns, and so explain some of the observed variation in stock prices. The large variation of stock price relative to consumption is a continuing area of intense interest in economics, commonly described as the equity premium puzzle. It is widely accepted that earnings follow the business cycle, which has a high correlation with the consumption cycle. At the same time, it is also accepted that most managers choose dividends to be a fraction of the "permanent" level of earnings (Lintner, 1956). So dividend growth will tend to be less volatile than earnings growth and tend to lag earnings. Yet it is the more volatile retained earnings, or non-dividend, component of earnings that drives innovations in future cash flow growth by way of new investment. Thus, opposite relations of expected dividend and earnings growth with respect to expected consumption risk will impart different information to the market, and so both impact expected return.

Dividend yield tends to have low predictive power for short run expected return, yet has high predictive power over long horizons. Lettau and Ludvigson (2005) find that correlated fluctuations in expected dividend growth and expected returns have offsetting effects on the log-dividend yield ratio; the find that dividend growth is the variable that better explains short run returns. The consumption-based findings of Boguth and Kuehn (2013) provide insight into the specific mechanism by which consumption growth volatility drives the covariance between dividend growth and expected return. But dividend growth is too smooth to adequately explain expected returns, so in this paper we examine both dividend and earnings growth.

Our empirical method follows Boguth and Kuehn (2013), henceforth known as BK. Our first empirical analysis creates a Markov model of consumption growth based on Bayesian beliefs about the mean and volatility of consumption growth. The model has two drift and two volatility states, in keeping with the empirical analysis of consumption states in Johannes, Lochester and Mou (2011). In this literature, the representative agent infers the state of the economy from observable data, as in Lettau, Ludvigson and Wachter (2008);

here, the first and second moments of expected consumption follow a Markov chain, such that the agent's prior beliefs determine his wealth-consumption ratio, which in turn impacts the pricing kernel. The empirical implication of the model is that changes in beliefs about the conditional moments of consumption are priced in the cross-section of stocks because the agent's choice of wealth-consumption ratio is affected.

Next, we study the relation between risk loadings and expected return at the firm level. This entails sorting the data to create quintile portfolios based upon risk loading of expected return on expected consumption growth volatility risk. We confirm the findings of BK that loading on expected consumption growth does not explain expected return, whereas the loading on expected consumption growth volatility does forecast cross-sectional differences in next period expected return. Furthermore, these firm level results show a negative price for consumption volatility risk, meaning that portfolio expected return decreases as portfolio loading on consumption volatility risk increases across portfolios.

We then examine the consumption volatility risk (CVR) factor created by BK, defined as the return from holding a zero portfolio with a long position in the value-weighted quintile of stocks with high risk loading and a short position in the value-weighted quintile with low risk loading. In our results, CVR shows a -4.8% annual return. For robustness, the CVR factor is added to regressions that include the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. We find that the CVR factor remains significant in the presence of all of these factor models. On the whole, our results for CVR are consistent with BK.

In our last series of tests, which produce our main results, we examine dividend growth and earnings growth across the risk loading quintile portfolios. We first examine dividend growth, in the manner of BK, and we then introduce new findings by also examining earnings. Within each quintile, the mean and volatility of expected dividend growth is regressed against the mean and volatility of expected consumption growth, respectively, where expectations are obtained via a Markov model. From the pattern of regression coefficients across quintiles, dividend growth volatility is shown to have a declining sensitivity to consumption growth volatility across the quintiles, whereas there is no relation between mean dividend growth and mean consumption growth[1]. Expected return has been shown to have the same pattern of decreasing across quintiles and, thus, BK assert that the negative price of risk is explained by the decline in sensitivity, or leverage, of dividend growth volatility to consumption growth volatility risk.

Stocks in the fifth quintile have the highest risk loading, meaning that they have the highest cost of consumption risk measured as change in expected return per unit change in consumption volatility; at the same time, this quintile of stocks has the lowest expected return and the lowest sensitivity of dividend growth volatility with respect to consumption growth volatility. The intuition here is that firms with a high cost of consumption risk maintain stable dividend growth regardless of consumption growth volatility, and this stability of cash flow to investors is reflected in low expected return.

In contrast, our results for earnings growth show an increasingly positive sensitivity to the volatility of consumption across quintiles, which is opposite to the pattern for dividends. Given that earnings growth and aggregate consumption growth are positively correlated, the inference here is that firms with a high cost of consumption risk maintain

[1] Although we confirm the insignificant sensitivity between the mean of dividend growth and the mean of consumption growth by using dividend per share, we find it is significant when using total amount of dividend.

stable dividend growth while, at the same time, increasing earnings growth in step with increasing aggregate consumption growth in the economy.

Moreover, to demonstrate the direct connection between dividends and earnings, we examine the payout ratio, dividends divided by earnings, by regressing the moments of the payout ratio against the respective moments of consumption growth across the portfolios of consumption risk loading. Across the portfolios, we find that the sensitivity between payout ratio growth volatility and consumption growth volatility decreases, similar to the pattern for dividends. The intuition here is that firms with a high cost of consumption risk tend to maintain a stable payout ratio regardless of consumption growth volatility. Thus, whereas most research focuses on the effects of dividend cash flows, we show that both dividends and earnings are intermediate variables between consumption and expected return, and so both drive changes in stock prices.

There is an ongoing debate in asset pricing literature about the relevance of earnings with respect to expected return (e.g. Ang and Bekaert, 2007, Sadka, 2007). The literature typically considers dividends to be a finance variable because it is a cash flow directly paid out to shareholders, while earnings are considered to be a lagging accounting variable and so possibly of lesser importance. However, if dividend cash flows represent the permanent component of earnings, then variation in earnings provides additional information about growth of future cash flows in the near to midterm of the economic cycle. By showing that expected return is impacted by both variables, this paper provides new insight about the puzzle of why stock returns are much more volatile than consumption.

The rest of the paper is as follows. Chapter 2 represents the body. Section 2.1 is a literature review. Section 2.2 describes the data set and variables. Section 2.3 presents the results. Section 2.4 suggests a direction for future research. Finally, Chapter 3 concludes.

Chapter 2 Body of Thesis

2.1 Literature Review

The equity premium puzzle was first proposed more than 30 years ago by Mehra and Prescott (1985) but, to this day, researchers in macroeconomics and finance continue to search for resolution of this phenomenon. Investors are seemingly compensated too much for undertaking risk. According to Campbell (2003), the annualized real average stock return in the US was 8.1% from 1947q1 to 1998q4, which was around 8 times higher than the annualized real return of 3-month Treasury bills. Modeling a utility function and Euler equation for consumption, Campbell (2003) shows that US data implies that relative risk aversion should be 240.647, but Mehra and Prescott (1985) consider the reasonable relative risk aversion range to be between 0 and 10. On the other hand, Shiller (1982) indicates large consumption volatility could explain the high stock return, but he also points out the observed consumption volatility is very smooth compared to the stock price volatility. Mehra and Prescott (2003) review the research work done from 1985 to 2003 and conclude that the problem remains unsolved. In plain terms, the ongoing research challenge is to explain the high volatility of stock returns relative to the volatility of aggregate consumption.

In pursuit of this question, a huge literature has evolved. Bansal and Yaron (2004) make use of Epstein and Zin's (1989) preference and develop the long run risk (LLR) model to articulate the importance of economic uncertainty in explaining equity premium puzzle. Their results are based on risk aversion of 10 and intertemporal elasticity of substitution (IES) of 1.5. Savov (2011) obtains a somewhat more realistic relative risk aversion of 17, by using garbage that households produce as the proxy for consumption. On the other hand, consumption is traditionally measured as the sum of services and non-durable goods. Bansal, Kiku, and Yaron (2007) make use of cross-section of returns to show that high risk aversion is the result of time averaging effects. BK explain the negative risk premium by showing a negative cross-sectional relationship between dividend growth volatility and consumption growth volatility. Recently, Bansal, Kiku, Shaliastovich, and Yaron (2014) provide evidence that there is bias in estimates of expected return when macroeconomic volatility is not controlled for. Tédongap (2015) shows that changes in consumption volatility explain much of the variation in asset pricing anomalies.

Within the consumption literature, it is a standard assumption that future return can be estimated from dividends, at least over the long term horizon. In theoretical models, aggregate consumption is financed by dividends generated from investments (Campbell, 2003). However, Bansal and Yaron (2004) find that aggregate market volatility risk is negative priced. BK find that aggregate consumption growth risk is negatively priced, and explain the negative price of risk by showing that firms with a higher price of consumption risk have both lower dividend growth volatility and lower expected return.

Outside of the consumption literature, Lamont (1998) documents that dividend payout ratio predicts future stock return as a result of the predictability of both dividend and earnings; dividend yield is positively related to excess returns, whereas earnings yield is negatively related. Fama and French (2002) examines the predictive power of dividend growth and earnings growth for expected return. Empirical evidence by Lewellen (2004) indicates that the dividend yield forecasts market returns; however, dividend variation does not explain all of the variation in stock returns in the short run. Menzly, Santos, and Veronesi (2004) find that varying risk preference over time reduces the predictability of dividend yield. Lettau and Ludvigson (2005) discover the covariation between expected returns and expected dividend growth over business cycle reduces the forecast capability of log dividend-price ratio. Campbell and Thompson (2008) examine the predictive power of various indicators versus the long term averages of dividend yield and earnings yield.

The predictive power of earnings is a continuing debate in asset pricing literature. Although Ang and Bekaert (2007) show that dividend yield predicts future excess return, they find weak evidence for the ability of earnings yield to predict future excess return. On the other hand, Sadka (2007) finds that expected earning is significantly and negatively associated with expected return. The impact of earnings on asset prices are examined in Ball, Sadka, and Sadka (2009) and Sadka and Sadka (2009).

The most relevant papers to our work are Lamont (1998) and BK, but we go beyond them to show that dividend growth volatility and earnings growth volatility have opposite relationships with consumption growth volatility while jointly impacting expected return. Our findings of opposite relationships of dividend and earnings to consumption provides an underlying mechanism for the Lamont (1998) findings of opposite relationships of earnings yield and dividend yield to future return. And where BK show that the negative price of consumption volatility risk can be explained by dividend cash flows, we use their methodology and extend their results to show that the negative price of consumption volatility risk reflects both dividend and earnings cash flows.

In showing that consumption connects to expected return via the conjoined effects of both dividend and earning cash flows, we contribute new insight as to why observed stock returns are much more volatile than consumption or dividends.

2.2 Data

In this section, we report the data sets used in the study as well as defining the key variables. Our samples are collected from five sources (BEA, CRSP, Compustat, Ken French, Federal Reserve). The data can be categorized as two types: (i) aggregate consumption growth, and (ii) financial data for individual firms and stock market indexes. The sample period is post WWII, from 1947 to 2014. The definitions of key variables are given in Lists of symbols, abbreviations or other[2].

For raw consumption data, we use the data set of BK for the time range of 1947q1 to 2009q4, and we extend it to 2014q4[3]. This consumption data is comprised of the sum of services and nondurable goods adjusted for seasonality, originating from the Bureau of Economic Analysis (BEA). To extend the data set to 2014, we download quarterly indexes from the BEA. Financial data is obtained from CRSP, Compustat, and the Kenneth R. French Data Library. The riskless rate and consumer price index (CPI) data are from the Federal Reserve.

We follow BK in restricting the data set of firm level observations. In the first instance, we extract most of the data from CRSP and only keep observations for which the share code is either 10 or 11 and exchange code is either 1 or 2. By doing so, we only retain firms' common stocks that are listed on the NYSE and Amex. In the second instance, companies that have no dividend distribution in a previous calendar year are eliminated. The method of Bansal, Dittmar, and Lundblad (2005) is used to calculate values for dividend payments and repurchases. The first step is to adjust the number of share outstanding (shrout) by using the cumulative factor to adjust shares (cfacshr). Then, we adjust monthly holding

[2] We did not repeatedly define variables that appear in multiple tables.
[3] We thank Oliver Boguth for providing this data on his web site.

returns without dividend (retx) downward if the ratio of current adjusted number of shares outstanding to previous is less than one. The retx will remain unchanged if the ratio is equal or greater than one. Finally, the adjusted distributions are measured as the product of stock price at the beginning of the period times the difference between monthly holding return (ret) and adjusted monthly holding return without dividend. In the third instance, every firm was required to have 10 years of valid return data, dropping firms that do not meet this criterion. We run a window of 10 years rolling time-series regressions for each firm. A firm's quarterly excess return is regressed on log consumption growth as well as the first and second moments of consumption growth. Therefore, firms that have no 10 years return data were dropped.

The data is organized into 4 main data sets for various tests:

(i) In our extended consumption data sample, the number of observations is 272 since they are quarterly data from 1947q1 to 2014q4. This data set is used to produce Table 1.

(ii) Our monthly firm-level data sample is collected from CRSP; the variables include PERMNO, Names Date (date), Share Code (shrcd), Exchange Code (exchcd), CUSIP Header (cusip), Price (prc), Returns (ret), Share Outstanding (shrout), Cumulative Factor to Adjust Share (cfacshr), Returns without Dividend (retx), and Dividend (divamt). There are a total of 421,140 observations after the aforementioned restrictions are applied for the time range from 1964m1 to 2014m12. These variables are used in conjunction with Compustat data to generate Table 2, Table 3, Table 4, Table 7, Table 8, Table 9, and Table 10.

(iii) We use both annual data and quarterly data from Compustat. The annual data from 1964 to 2014 consist of gvkey, cusip, Common/Ordinary Equity (ceq), and Deferred Taxes (txdb), while the quarterly data from 1964q1 to 2014q4 consist of gvkey, cusip, and Income Before Extraordinary Items (ibq). In addition, the sum of ceq and txdb is taken to be book equity (Boguth & Kuehn, 2013), which helps us to find book-to-market ratio (BM). When the BM is merged to the CRSP monthly firm-level sample, there is a total of 331,875observations. Our last four tables use earnings before extraordinary items, ibq, (113,671 observations) and quarterly firm-level dividend (131,612 observations).

(iv) Finally, the 4 Fama-French risk factors are obtained from the Kenneth R. French Data Library: Market risk premium (MKT), Size (SMB), Value (HML), and Momentum (MOM). These risk factors are based on monthly data from 1964m1 to 2014m12, resulting in a total of 612 observations, used in Table 5 and Table 6.

2.3 Empirical Analysis

We use the extended sample to replicate most of the tables of BK. First, our Table 1 reports all the parameters that were estimated from Multivariate Markov Model for our extended consumption dataset with a period from 1947q1 to 2014q4. Since we use a window of 5 years to measure the first and second moments of consumption growth, the final output for the mean and the standard deviation is the period 1952q2 to 2014q4.

The purpose of using the Markov model is to mitigate noise in consumption and related variables. Empirical literature, such as Breeden, Gibbons, and Litzenberger (1989) and Wilcox (1992), indicates that aggregate consumption data, which is defined as the sum of service and nondurable goods, has noise. The consumption variable is time-series data with a nonstationary process. Therefore, the non-stationarity will cause the statistical inference that is drawn from ordinary least-squares (OLS) estimation to have a bias. Although we could take the first difference of the nonstationary time-series data to obtain a stationary time-series, Hamilton (1989) suggests that it is better to model macroeconomic series through a Markov switching model because the business cycle shifts between contraction state and expansion state. Even though the transition between these two states is unobservable, it follows a Markov chain process. Therefore, we choose the Markov model as the best representation of expected consumption.

BK use a Multivariate Markov Model, instead of the standard Univariate Markov Model, because their equation 10 shows log total consumption growth variable (Δc_{t+1}) is constructed by using log service consumption growth (Δs_{t+1}), minus changes in the log service consumption share (Δv_{t+1}). They indicate that “it is not possible to recover total consumption growth from the dynamics of service and nondurable consumption growth alone” (Boguth and Kuehn, 2013, p. 2596). Thus, the Multivariate Markov Model is employed by them to measure the first and second moments of consumption growth as shown in their Table I.

$$\Delta c_{t+1} = \Delta s_{t+1} - \Delta v_{t+1} \quad (10)$$

We thank Oliver Boguth for providing us with the Matlab programming codes to run the Multivariate Markov Model. The parameters that we obtain from the Markov process are similar to the results of BK. Panel A of Table 1 shows expected service consumption growth in the high state (0.77%) to be more than two times larger than in the low state (0.34%).

Expected service consumption volatilities are 0.21% in low state and 0.46% in high state. Our Panel B, which shows parameters of expected service consumption share, has small differences with BK. The growth parameter in the low state is negative (-0.0060%) in this paper, whereas it is positive (0.0042%) in BK; other parameters are similar. Expected service consumption share growth is 0.09% in high state, and the volatilities are 0.10% in low state and 0.24% in high state. Panel C shows the marginal transition probabilities to remain in low state are 0.94 for first moment of consumption growth and 0.95 for the second moment, while the probabilities to stay in high state are 0.95 and 0.97 for the first and second moments of consumption growth, respectively.

Table 1: Markov Model of Consumption Growth[4]

This table is generated from an extended consumption data set with a time range from 1947q1 to 2014q4. Matlab code and adjusted consumption data with a time range between 1947q1 and 2009q4 is obtained from Oliver Boguth. Consumption data for 2010q1 to 2014q4 is generated from quarterly indexes of seasonally adjusted real personal consumption expenditure taken from the Bureau of Economic Analysis (BEA). The Multivariate Markov Model estimation follows Hamilton (1994).

[4] We replicate and extend Table I of Boguth and Kuehn (2013).

Panel A: Service Consumption (%)			
μ_l^s	μ_h^s	σ_l^s	σ_h^s
0.3435	0.7718	0.2102	0.4562
(0.0287)	(0.0410)	(0.0233)	(0.0347)
Panel B: Service Consumption Share (%)			
μ_l^v	μ_h^v	σ_l^v	σ_h^v
-0.0060	0.0872	0.1041	0.2417
(0.0150)	(0.0177)	(0.0167)	(0.0181)
Panel C: Marginal Transition Probabilities			
p_μ^{ll}	p_μ^{hh}	p_σ^{ll}	p_σ^{hh}
0.9358	0.9479	0.9531	0.9664
(0.0209)	(0.0166)	(0.0120)	(0.0032)
Panel D: correlation			
		ϱ_{sv}	
		0.1527	
		(0.0671)	

Standard error in parentheses

We follow the methodology of BK, using regression and portfolio sorts methods, to show that the second moment of consumption growth is negatively priced. Firstly, we generate risk loadings in terms of their Equation (12), shown below. Every firm's quarterly excess return ($R_t^i - R_t^f$) is regressed on the change in log consumption growth (Δc_t) as well as the change in the first ($\Delta\widehat{\mu}_t$) and second ($\Delta\widehat{\sigma}_t$) moments of consumption growth, using a 10 year rolling time-series window of regressions.

$$R_t^i - R_t^f = \alpha_t^i + \beta_{c,t}^i \Delta c_t + \beta_{\mu,t}^i \Delta\widehat{\mu}_t + \beta_{\sigma,t}^i \Delta\widehat{\sigma}_t + \varepsilon_t \ (12)$$

The coefficients estimated from the rolling time-series regressions are collected as the risk loadings. Since the first 40 quarterly excess returns are from 1954q1 to 1963q4, the resultant risk loadings for the three variables span the period 1964q1 to 2014q4. Table 2 shows the portfolio return for monthly firm-level data set sorted into 5 portfolios at the end of every quarter based on ranked risk loadings. Table 2 replicates BK for the purpose of showing that we get similar results for the extended data set used in this paper.

Table 2: Return of Portfolios Formed on Risk Exposure[5]

This table shows portfolio return for when firms are sorted into 5 portfolios on the basis of risk loadings of excess return on consumption growth volatility risk, as per Equation (12) of BK. First, risk loadings are estimated by using a moving window of 10 years to regress every firm's quarterly excess return on change in log consumption growth, change in expected mean of consumption growth, and change in expected standard deviation of consumption growth. Then, return is calculated for the resultant portfolios. The sample time period is from January 1964 to December 2014.

The table shows both equally-weighted (EW) and value-weighted (VW) average monthly return for the 5 portfolios. The sorted portfolios of Panel A, Panel B, and Panel C are based on the three risk loadings, respectively. The last column (High- Low) of every panel is calculated as the net return of a zero portfolio with a 1 year holding period, simultaneously taking a long position in the HIGH sorted portfolio and a short position in the LOW sorted portfolio, where LOW and HIGH represent the magnitude of the estimated risk loading coefficients. The t-statistics are reported in parentheses, measured using Newey and West (1987) adjusted standard errors with 12 lags.

We thank Oliver Boguth for offering tips in creating this table.

[5] We replicate and extend Table IV of Boguth and Kuehn (2013).

Panel A: Univariate Sorts Based on $\beta_{c,t}^{i}$						
	LOW		MED		HIGH	High-Low
EW	1.34	1.21	1.20	1.14	1.13	-0.21
	(7.63)	(8.52)	(7.90)	(6.34)	(4.59)	(-0.79)
VW	1.10	1.03	0.94	0.82	0.89	-0.21
	(7.66)	(7.42)	(6.49)	(4.64)	(3.85)	(-0.93)
Panel B: Univariate Sorts Based on $\beta_{\mu,t}^{i}$						
	LOW		MED		HIGH	High-Low
EW	1.22	1.20	1.17	1.17	1.26	0.04
	(6.03)	(7.37)	(8.04)	(7.33)	(6.76)	(0.21)
VW	1.11	1.03	1.01	0.84	0.91	-0.20
	(5.77)	(6.66)	(7.73)	(5.20)	(5.37)	(-1.08)
Panel C: Univariate Sort Based on $\beta_{\sigma,t}^{i}$						
	LOW		MED		HIGH	High-Low
EW	1.40	1.25	1.17	1.10	1.08	-0.32
	(6.21)	(7.56)	(8.08)	(7.47)	(6.60)	(-1.81)
VW	1.24	0.99	0.93	0.91	0.83	-0.40
	(6.35)	(6.37)	(6.48)	(6.20)	(4.61)	(-2.38)

t statistics in parentheses

Table 2 shows the returns of both equally-weighted (EW) and value-weighted (VW) monthly portfolios. Panel A and Panel B show portfolio returns when firms are sorted into portfolios based on risk loadings of change in log consumption growth and change in expected mean of consumption growth, respectively; the returns of the High-Low zero portfolios in the last column are nil, indicating that the changes in the level and mean of consumption growth do not impact investors' expectations of future return. On the other hand, for changes in expected volatility of consumption growth, Panel C of Table 2 shows a pattern of monotonic decrease in expected portfolios return, similar to the findings of BK. In Panel C, the EW portfolio return decreases from 1.4% to 1.08% while the VW portfolio return decreases from 1.24% to 0.83%. For the High-Low zero investment portfolios, the expected monthly holding return is -0.32% for the EW portfolio and -0.4% for VW portfolio. The zero investment portfolio result is statistically significant at a 90% confidence level for the EW portfolio, and it is statistically significant at a 95% confidence level for the VW portfolio. BK define the VW High-Low portfolio as the consumption volatility risk (CVR) factor, proposing the CVR as a new risk factor that is distinct from other well-known risk factors; following BK, we test CVR against other risk factors in Table 5 and Table 6 below.

We do not replicate Table II and Table III of BK because we consider that the related methodology produces biased results. To explain further, Table II of BK employs three types of portfolio excess return as test assets to check price implications for change in log consumption growth, as well as checking implication of change in the first and second moments of consumption growth through two-pass regressions. The first type of portfolio is 25 Fama-French size and book-to-market portfolios; the second type is 40 industry and book-to-market portfolios; and the last is 25 net share insurance and size portfolios. Although Table II of BK shows return predictability associated with change in consumption growth volatility, Lewellen, Nagel, and Shanken (2010) show that using such test assets induces bias in asset pricing results. Therefore, BK use firm-level data, not test assets, to study consumption growth risk factors via Fama-MacBeth regressions and portfolio sorts. The results of BK estimated in Fama-MacBeth regressions (Table III in their paper) suggest that the second moment of consumption growth is negatively priced. However, BK consider the presence of an errors-in-variables problem for risk loadings that are estimated from a rolling time-series window in Fama-MacBeth regression, which makes such research results less convincing due to possible false standard errors. On the other hand, BK show that the portfolio sorts method offers conservative statistical inference since the standard errors are underestimated. For these reasons, we use only the portfolio sort method, shown above in our Table 2.

Having used portfolio sorts to demonstrate that consumption growth volatility is negatively associated with stock returns, as in their Table IV, BK report descriptive statistics in their Table V for the 5 portfolios that sorted based on the risk loadings of consumption growth volatility. We replicate and extend their Table V in our sample and see similar results in our Table 3.

The Panel A of our Table 3 gives descriptive statistics for average risk loading, value-weighted portfolio return, and standard deviation and skewness for the 5 sorted VW portfolios. The average risk loadings increase from -0.27 for LOW sorted portfolio to 0.20 for the HIGH portfolio. The average VW portfolio returns are same as in Panel C of Table 2, which decreases from 1.24% in the LOW portfolio to 0.83% in the HIGH portfolio. Furthermore, both the Table V of BK and our Table 3 show that the standard deviation of the VW portfolio returns exhibits a U-shaped pattern. However, we find a smaller magnitude of return skewness in the 5 sorted portfolios compared to BK.

Panel B of Table 3 reports market share, market equity (ME), book-to-market ratio (BM), and momentum (MOM) for the 5 portfolios. The HIGH portfolio, which has the highest consumption growth volatility risk loadings in Table 2, has higher market share, larger ME, lower BM, and lower MOM than others in Table 3; the same phenomenon is reported by BK. Normally, firms have only one book equity value in a calendar year; however, some firms may change their accounting period during a calendar year, which results in multiple equity values and, therefore, we select the last record in a calendar year to calculate BM. Panel B of our Table 3 indicates that the portfolio average BM decreases from 0.87 in the LOW portfolio to 0.79 in the HIGH portfolio, similar to the Table V of BK where it decreases from 0.85 to 0.74. Lastly, momentum (MOM) is defined as previous 12 months cumulative return. In our sample, the portfolio average MOM decreases from 14.91% in the LOW group to 11.28% in the HIGH group, whereas BK show smaller MOM decreasing from 10.67% to 6.72%.

Table 3: Characteristics of Consumption Volatility Risk Portfolios[6]

Following the methodology of BK, this table reports descriptive statistics for the sorted portfolios of Panel C in Table 2. These portfolios are sorted based on the risk loadings on consumption growth volatility. Panel A shows the average risk loadings (β_σ), value-weighted average monthly returns, and standard deviation and skewness for each portfolio. Panel B shows market share, market equity (ME), book-to-market ratio (BM), and momentum (MOM) for each portfolio. The sample time period is from January 1964 to December 2014.

[6] We replicate and extend Table V of Boguth and Kuehn (2013).

Panel A: Univariate Sort Based on $\beta^i_{\sigma,t}$						
	LOW		MED		HIGH	High-Low
β_σ	-0.27	-0.11	-0.03	0.05	0.20	0.47
Return	1.24	0.99	0.93	0.91	0.83	-0.40
St. Dev.	4.26	3.56	3.46	3.53	3.92	3.18
Skewness	-0.13	-0.16	-0.04	-0.18	-0.18	0.41
Panel B: Characteristics of Sorts Based on $\beta^i_{\sigma,t}$						
	LOW		MED		HIGH	High-Low
Market Share (%)	12.70	18.10	21.64	22.85	24.70	12.00
ME	448.18	638.87	763.65	806.34	871.77	423.59
BM	0.871	0.830	0.823	0.792	0.791	-0.08
MOM	14.91	13.16	12.05	11.45	11.28	-3.63

Table VI of BK demonstrates that asset pricing anomalies, which usually appear in small or illiquid stocks, are not the reasons why consumption volatility risk is negatively priced. Following their approach, we first sort all the firms into 3 groups based on the risk loadings of consumption growth volatility (LOW, MED, HIGH). Then we further subdivide each one of the 3 groups into 6 groups (for a total of 18 groups) based on market capitalization (ME), book-to-market ratio (BM), and momentum (MOM), respectively, as given in our Table 4, with monthly value-weighted portfolio returns reported in each panel. In the Panel A of Table 4, the average return of portfolios that have smaller ME is greater than for portfolios that have bigger ME. As would be expected, Panel B and Panel C show higher returns for portfolios with bigger BM or MOM. Our results are similar to BK, as the patterns shown in our Table 4 are the same as theirs, and the values of monthly portfolio returns are similar as well. In addition, the last column of each panel gives High-Low, which is the 1 year holding returns of a zero portfolio that is short LOW and long HIGH. The High-Low return is not statistically significant for the groups of small firms and low BM firms. More importantly, the magnitude of all High-Low return values in Table 3 are all of the same sign and of approximately the same magnitude as the High-Low values in Table 4, which is evidence that asset pricing anomalies do not distort returns to decrease in small subgroups of our sample.

Table 4: Portfolios Formed on Consumption Volatility Risk and Characteristics[7]

Following BK, the LOW, MED, and HIGH portfolios sorted on the risk loadings of consumption volatility ($\beta\sigma$) firms are further divided into 6 groups based on characteristics of market capitalization, BM, and MOM. Panel A shows average value-weighted monthly returns for $\beta\sigma$ and market capitalization sorted portfolios. Panel B indicates average value-weighted monthly returns for $\beta\sigma$ and BM ratio sorted portfolios. Panel C illustrates the average value-weighted monthly returns for $\beta\sigma$ and MOM sorted portfolios. The sample time range is between January 1964 and December 2014. All t-statistics are reported in parentheses, measured using Newey and West (1987) adjusted standard errors with 12 lags.

[7] We replicate and extend Table VI of Boguth and Kuehn (2013).

Panel A: Market Capitalization				
	LOW	MED	HIGH	High-Low
Small	1.439	1.245	1.237	-0.202
	(7.81)	(8.87)	(9.03)	(-1.69)
Big	1.126	0.912	0.896	-0.230
	(7.69)	(7.22)	(6.05)	(-2.12)
B-S	-0.312	-0.333	-0.341	
	(-2.84)	(-3.70)	(-3.14)	
Panel B: Book-to-Market Ratio				
	LOW	MED	HIGH	High-Low
Low BM	1.018	0.858	0.851	-0.168
	(6.69)	(6.30)	(5.70)	(-1.51)
High BM	1.361	1.089	1.031	-0.330
	(9.05)	(8.60)	(7.80)	(-2.84)
H-L	0.343	0.231	0.181	
	(3.52)	(2.30)	(1.98)	
Panel C: Momentum				
	LOW	MED	HIGH	High-Low
Low MOM	1.053	0.845	0.809	-0.244
	(6.32)	(6.16)	(5.35)	(-2.24)
High MOM	1.227	1.015	0.978	-0.249
	(8.32)	(7.84)	(6.55)	(-2.24)
H-L	0.174	0.169	0.169	
	(1.92)	(1.97)	(1.79)	

t statistics in parentheses

We next show that consumption growth volatility can explain variation in expected return over and above what is explained by the 4 well-known risk factors: market risk premium (MKT), size (SMB), value (HML), and momentum (MOM). To create a risk factor data set, we take our value-weighted portfolio High-Low holding return which is reported in Panel C of Table 2, which BK defines as the consumption volatility risk (CVR) factor, and then merge it with the four risk factors that are obtained from the Kenneth R. French Data Library, for the time period between 1964m1 to 2014m12.

Summary statistics for all 5 risk factors are given in Panel A of Table 5, reporting mean return (%), standard deviation (%), and Sharpe ratio. The MOM portfolio has the largest mean return in magnitude, while MKT is the most volatile in terms of standard deviation, and absolute value of Share ratio is highest in CVR column. The correlation matrix between these 5 risk factors is shown in Panel B. Most of the correlation coefficients are similar to BK except in the correlation between CVR and MKT, where we see a positive relationship while they report a negative relationship. On the other hand, the correlation between CVR and MKT is insignificant in our table; while BK do not show the significance level in their paper, we believe it is likely similarly insignificant because of the regression results that are shown in Panel C of their Table VII.

Panel C of our Table 5 has three specifications where CVR is regressed on the other 4 well-known risk factors in order to illustrate that the CVR cannot be subsumed by the other risk factors. In the first regression column, the CVR is only regressed on MKT, and the coefficient on MKT is positive but insignificant. Though the positive sign is opposite to BK, their coefficient on the MKT is also insignificant. Similarly, we both have negative adjusted R^2 for this specification. The sign on MKT in the first specification is the only material difference between our Panel C of Table 5 and the results of BK Table VII. In the second column, where we add SMB and HML to create the second specification, all coefficients including MKT become negative. Although the coefficient on HML is significant, the adjusted R^2 is only 4.96%. Lastly, in the third column, MOM is included with other three risk factors to generate the third specification. When CVR is regressed on all 4 well-known risk factors, only the coefficient on HML is statistically significant at a 95% confidence level. Again, the adjusted R^2 for the third specification is only 6% in our sample, meaning that 94% of CVR is unexplained. Therefore, our Panel C of Table 5 confirms that the well-known risk factors do not explain the variation in the CVR factor.

Table 5: CVR versus Other Risk Factors[8]

Following the methodology of BK, we compare the CVR factor with market risk premium (MKT), size (SMB), value (HML), and momentum (MOM). The CVR is a 1 year zero portfolio holding return from simultaneously holding a long position in the HIGH portfolio and a short position in the LOW portfolio. As shown in Panel C of Table 2, the CVR portfolios are sorted based on consumption volatility risk loadings, and their average returns are value-weighted. Panel A of this table shows mean, standard deviation, and Sharpe ratio for the CVR, MKT, SMB, HML, and MOM risk factors. Panel B shows correlations between these 5 risk factors. Panel C shows time-series regressions. The sample time period is between January 1964 and December 2014. All t-statistics that are reported in parentheses, measured using Newey and West (1987) adjusted standard errors with 12 lags.

Panel A: Summary Statistics					
	CVR	MKT	SMB	HML	MOM
Mean (%)	-0.40	0.50	0.25	0.36	0.69
Std. Dev (%)	3.18	4.47	3.12	2.87	4.24
Sharpe Ratio	-0.13	0.11	0.08	0.13	0.16

[8] We replicate and extend Table VII of Boguth and Kuehn (2013).

Panel B: Correlations					
	CVR	MKT	SMB	HML	MOM
MKT	0.0205				
	(0.6135)				
SMB	-0.0651	0.3106			
	(0.1075)	(0.0000)			
HML	-0.2027	-0.2998	-0.2266		
	(0.0000)	(0.0000)	(0.0000)		
MOM	-0.0705	-0.1254	-0.0026	-0.1558	
	(0.0815)	(0.0019)	(0.9485)	(0.0001)	

Panel C: Time-Series Regressions of CVR on Other Factors			
	CAPM	Three-Factor	Four-Factor
	CVR	CVR	CVR
MKT	0.0145	-0.00996	-0.0256
	(0.30)	(-0.33)	(-0.94)
SMB		-0.116*	-0.115
		(-1.67)	(-1.53)
HML		-0.257**	-0.284**
		(-2.16)	(-2.44)
MOM			-0.0863
			(-1.39)
_cons	-0.412**	-0.278*	-0.201
	(-2.37)	(-1.70)	(-1.26)
N	612	612	612
adj. R^2 (%)	-0.12	4.96	6.06

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table VIII of BK employs two-pass regressions to demonstrate that consumption volatility risk (CVR) factor has the ability to explain portfolio returns, while holding 4 well-known Fama-French risk factors constant. The 4 risk factors are held approximately constant by way of creating portfolios sorted on those factors. We replicate and extend their Table VIII using the same approach with our data sample and obtain similar results in our Table 6.

First, using monthly data, we create 35 test assets, which consists of 5 monthly portfolios created by sorting based on consumption growth volatility risk loadings, and 10 monthly portfolios for each of three factors consisting of firm market capitalization, book-to-market ratio, and momentum. Monthly value-weighted returns are generated for all 35 test assets. Then, in the first pass regression, we regress the test asset monthly return on CVR and the 4 Fama-French risk factors: namely, market risk premium (MKT), firm size (SMB), value (HML), and momentum (MOM). Risk loadings of these factors are collected and used in the second pass regressions as independent variables, where portfolio excess return (ER) is now the dependent variable. The results of the second pass regressions are shown in Table 6. In column (1), portfolio excess return is only regressed on risk factor loadings for MKT. SMB and HML risk loadings are added in column (2), and MOM risk loadings are added in column (3). The R^2 of the first three regressions are 0.02, 0.59, and 0.73, respectively. In columns (3) to (6), when CVR risk loadings are added in these three regressions, their R^2s increase dramatically to 0.14, 0.67, and 0.80, respectively. This significant increase in R^2s demonstrates the ability of consumption growth volatility to forecast expected return.

Table 6: Volatility Risk Factor Pricing[9]

Following the methodology of BK, we make use of 35 test assets to perform two-pass regressions. The first pass regressions that estimate risk loadings are not reported. This table reports the results of second-pass regressions that use excess return as the dependent variable and related risk loadings as the independent variables. The 35 portfolio average excess returns (ER) are regressed on risk loadings of the consumption volatility risk factor (CVR), and of 4 Fama-French risk factors, namely, market excess return (MKT), size (SMB), value (HML), and momentum (MOM). The 35 test assets consist of 5 value-weighted portfolios sorted on consumption volatility risk loadings, and 10 value-weighted portfolios sorted on each of size, momentum, and book-to-market ratio, respectively. The sample time period is from January 1964 to December 2014. We adjusted standard error in the first pass regressions in terms of Newey and West (1987) using 12 lags.

[9] We replicate and extend Table VIII of Boguth and Kuehn (2013).

	(1)	(2)	(3)	(4)	(5)	(6)
	ER	ER	ER	ER	ER	ER
MKT	-0.582	-0.0795	-0.0933	-0.627	-0.146	-0.155
	(-0.90)	(-0.18)	(-0.25)	(-1.02)	(-0.36)	(-0.48)
SMB		0.447***	0.483***		0.413***	0.450***
		(3.41)	(4.47)		(3.43)	(4.72)
HML		0.376**	0.425***		0.393**	0.439***
		(2.12)	(2.91)		(2.43)	(3.43)
MOM			0.494***			0.478***
			(3.99)			(4.39)
CVR				-0.495**	-0.406**	-0.380***
				(-2.10)	(-2.67)	(-3.17)
_cons	1.086**	0.642*	0.668**	1.064**	0.642*	0.667**
	(2.14)	(1.85)	(2.35)	(2.20)	(2.03)	(2.67)
N	35	35	35	35	35	35
R^2	0.024	0.591	0.733	0.142	0.669	0.802

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

BK point out that dividend cash flows can explain their empirical finding that consumption volatility is negatively priced[10]. It is generally accepted that the intertemporal elasticity of substitution should be greater than the inverse of relative risk aversion, which

[10] Bansal and Yaron (2004) find consumption volatility is negatively priced.

implies that a representative agent requires a higher risk premium when dividend growth volatility and consumption growth volatility are positively related. Our Table 7 below shows that the sensitivity between the dividend growth volatility and the consumption growth volatility decreases as the risk loadings of excess return on the second moment consumption growth increases. Furthermore, our Table 2, Panel C, shows that the risk premium for consumption volatility risk decreases monotonically across quintiles sorted on risk loading. The economic intuition here is that investors require lower risk premium for firms whose dividend growth volatility has lower sensitivity to consumption volatility risk. Although theory also predicts that the mean expected dividend growth should be positively related to expected consumption growth, the results in Table 7 does not support this prediction, as High-Low is insignificant in Panel A for mean dividend growth.

We replicate Panel A of Table IX of BK to show the concurrent trends of risk loading of expected return on consumption risk, and of the sensitivity of expected dividend cash flow to consumption risk. The objective here is to show that the pattern of dividend cash flow mirrors the pattern of expected return, thereby showing that expected dividend cash flow is the intermediate variable connecting consumption to expected return, and so provide an explanation for the observed negative risk premium associated with increasing consumption risk. First, we generate quarterly dividend per share for all firms. Then we create value-weighted portfolio dividends for the 5 portfolios sorted based on the risk loadings of expected return on consumption growth volatility. The nominal amounts of portfolio dividends are converted into real values by adjustment with the Consumer Price Index. Furthermore, in order to smooth the dividend growth series, we follow BK in applying a moving average window of 4 quarters to dividend growth. Thereafter, we implement a

Univariate Markov Model for the dividend growth in each portfolio and generate its first and second moments using a moving window of 5 years. During the Markov process, we assume that the transition is between two unobserved states and allowed dividend growth to vary between these two states. Finally, two time-series regressions are estimated in every portfolio: the first moment of dividend growth is regressed on the first moment of consumption growth; likewise, the second moment of dividend growth is regressed on the second moment of consumption growth.

Our replication is generally consistent with BK. The sensitivity parameter ($\emptyset_{\sigma}$) between the second moments of dividend growth and consumption growth shows a divergence pattern from the Low β_{σ} portfolio to the High β_{σ} portfolio, and the difference is statistically significant at the 95% confidence level. The intuition here is that people require less return as the correlation between consumption growth volatility and dividend growth volatility decreases. Similar to BK, we find the divergence for the first moment sensitivity ($\emptyset_{\mu}$) is insignificant; this lack of significance is puzzling because theory predicts a positive relationship. Lastly, in the descriptive statistics at the top of the table, expected average dividend growth (Mean %) shows a monotonic decrease pattern from the Low β_{σ} portfolio to the High β_{σ} portfolio, with values greater than what BK report in their Panel A of Table IX. One possible explanation for our greater values is that BK use cash dividend, whereas we calculate our dividend values as all distributions in dollar amount.

Table 7: Cash Flow Risk[11]

Following the methodology of BK, the top 2 rows of the table report descriptive statistics of average expected first and second moments of dividend growth for the 5 portfolios sorted based on consumption volatility risk loadings. In the lower rows of the table, the sensitivities of the dividend growth moments to expected first and second moments of consumption growth are reported. Time-series regressions are measured within each portfolio. The sample time period is between 1964q1 and 2014q4.

$$\mu_{i,t}^{d} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t;\ \ \sigma_{i,t}^{d} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t \text{ (Boguth \& Kuehn, 2013)}$$

Panel A: Dividend Cash Amount

	Low β_σ		Med β_σ		High β_σ	High-Low
Mean (%)	8.66	5.73	4.61	4.49	3.30	-5.36
Std. Dev. (%)	6.90	2.82	2.39	3.10	2.52	-4.38
$\emptyset_\mu$	-0.0217**	0.00261	0.0193***	-0.00697***	-0.0172***	0.00449
	(-2.30)	(1.04)	(5.45)	(-2.63)	(-6.76)	(0.45)
$\emptyset_\sigma$	0.00874	0.00279	-0.0255***	-0.00729***	-0.0251***	-0.0339**
	(0.58)	(1.18)	(-3.51)	(-2.65)	(-11.98)	(-2.21)

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

In the tables that follow, we examine the impact of earnings on expected return. Cash dividends are the portion of earnings that is received by shareholders, but the remaining portion is retained by the firm for reinvestment. While the firm's management has the discretionary authority pay out earnings as dividends or retain to reinvest, all earnings ultimately belong to the shareholders of the firm. However, firms are entities with an infinite

[11] We replicate and extend Panel A of Table IX of Boguth and Kuehn (2013).

lifetime, whereas shareholders are human beings who wish to maximize their lifetime utility. Hence, there is a trade-off between paying out earnings as a dividend or retaining earnings for reinvestment. Campbell (2003) presents a standard theoretical framework where aggregate consumption is essentially equal to dividends over the long term and expected dividends drive expected return; but it is accepted that that actual dividends are too smooth to explain the observed short run variation in stock returns. However, earnings might play a role in explaining the variation in stock returns, by way of investor expectations for the portion of earnings that is reinvested. What's more, Lamont (1998) find dividends yield is negatively related to future return, whereas earnings yield is positively related, results that suggest a role for earnings to explain expected return. On the other hand, using similar methodology to Lamont (1998), Ang and Bekaert (2007) find that earnings yield has predictive power in the data period used by Lamont (1998) but has no predictive power when a longer data period is used. However, much other literature (e.g. Sadka (2007); Sadka (2009); Sadka and Sadka (2009)) supports the ability of earnings to forecast future return. This paper contributes to this literature by examining the role of earnings as a connecting variable between consumption and expected return.

We take earnings to be equal to total quarterly income before extraordinary items (ibq), Total quarterly earnings per firm are used in Table 8. We use total quarterly earnings per firm because we are trying to link accounting data with equity return. However, we are not the first attempt. Feltham and Ohlson (1995) is the first to reveal the valuation role of earnings; therefore, we follow them to use earnings instead of earnings per share. For Table 8, first, we construct value-weighted earnings for the 5 portfolios sorted on risk loading of expected return on consumption, and convert nominal earnings into real earnings. Second, the earnings growth of each portfolio is smoothed through a rolling average window of 4 quarters. Third, the Univariate Markov model is applied to the earnings growth in every portfolio, and the first and second moments of earnings growth are estimated with a moving window of 5 years. Lastly, the first and second moments of earnings growth are regressed on corresponding first and second moments of consumption growth, respectively, in each portfolio.

In Table 8, we report average expected first and second moments of earnings growth as well as time-series regression parameters. The mean expected growth in portfolio earnings monotonically decreases from 9.96% in the Low β_σ portfolio to 4.53% in the High β_σ portfolio, where β_σ is the risk loading of expected return on consumption volatility risk. These results show the same pattern as previously seen for average expected dividend growth, which decreases from 8.66% to 3.3% in our Table 7. However, there are two differences. First, the covariance between mean expected earnings growth and expected consumption growth is converging as the consumption risk increases, moving from -2.07% in the Low β_σ portfolio to 0.29% in the High β_σ portfolio. The cross-sectional difference for mean earnings (High-Low for $\emptyset_\mu$) growth is statistically significant, which is in contrast to the insignificance for mean dividend growth shown in Table 7. Looking at second moments in the table ($\emptyset_\sigma$), the same pattern of negative to positive sensitivity appears in the covariance between the second moment of earnings growth and the second moment of consumption growth. It increases from -6.45% in the Low β_σ portfolio to 0.38% in the High β_σ portfolio, and the High-Low sensitivity difference is statistically significant as well.

Table 8: Earnings Risk

We reported the expected first and second moments of earnings growth for the 5 portfolios that sorted based on consumption volatility risk loadings. Also, their sensitivities to expected first and second moments of consumption growth are reported. Time-series regressions are measured within each portfolio. The sample time range is between 1964q1 and 2014q4.

$$\mu_{i,t}^{ibq} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^{ibq} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

Income Before Extraordinary Items (ibq)						
	Low β_σ		Med β_σ		High β_σ	High-Low
Mean (%)	9.96	8.48	7.46	6.32	4.53	-5.43
Std. Dev (%)	4.00	2.82	1.46	1.65	1.76	-2.23
$\emptyset_\mu$	-0.0207***	-0.0000312	0.00127	0.0172***	0.00291*	0.0236***
	(-3.67)	(-0.01)	(0.68)	(6.43)	(1.74)	(4.18)
$\emptyset_\sigma$	-0.0645***	-0.00527**	-0.00741***	0.0163***	0.00377**	0.0683***
	(-10.09)	(-2.07)	(-4.58)	(7.57)	(2.31)	(11.94)

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 8 provides strong evidence for the predictability of earnings. As the sensitivity between earnings growth volatility and consumption growth volatility moves from negative to positive, the risk premium on consumption risk decreases across quintiles. In other words, investors require less risk premium for firms whose mean earnings growth has high positive covariance with mean consumption growth. Furthermore, as compared to dividend growth in Table 7, the earnings growth volatility shows an opposite pattern of covariance with consumption growth volatility; the sensitivity of earnings growth volatility increases from the Low β_σ portfolio to the High β_σ portfolio. The opposite pattern between dividends and earnings is consistent with Lamont's (1998) observation that dividend yield has a positive relation with future return and earnings yield has negative relation. Lamont offers some explanation of this opposite pattern by observing that dividends are the permanent component of earnings while earnings fluctuate with the economic cycle. In Table 8, we show empirical evidence that earnings and consumption tend to move together as the consumption risk increases, which supports Lamont's explanation that earnings' predictive power stems from its positive covariance with business condition. Therefore, investors require a lower risk premium for firms in the High β_σ portfolio because, not only is the dividend growth less influenced by consumption risk as shown in Table 7, earnings growth concurrently varies positively with the consumption risk as shown in Table 8. Our explanation for the opposite patterns for dividends and earnings is that dividends are the permanent component of cash flow paid out to shareholders, but earnings includes the retained component of cash flow that is reinvested for future growth.

We conduct several robustness checks in Table 9 in order to rule out potential sample selection bias in Table 8, where we have fewer observations after going from dividends to earnings data. The data set of Table 9 is generated subject to the requirement that observations must have data for both dividends and earnings; because the resulting observations are sparse in early years, the sample period is shortened to be from 1972 to 2014. The need to shorten the sample period arises because Compustat and CRSP are not perfectly matched, especially in early years. Table 9 also uses total quarterly cash flows per firm instead of per share data; Panel A uses total quarterly earnings firms, Panel B uses total quarterly dividends per firm, and Panel C uses total quarterly retained earnings per firm.

Quarterly dividend per share is used in Table 7, while total amount of quarterly net income of each firm is utilized in Table 8. Therefore, in order to make a more meaningful comparison, in Table 9 we use total quarterly cash flow per firm for all observations; we convert the quarterly dividend per share to a total amount of dividends[12] that each firm has distributed per quarter. Moreover, the statement of retained earnings is constructed by adding net income and deducting dividends from beginning retained earnings to arrive ending retained earnings. Therefore, we use a panel data set in Table 9 containing total retained earnings growth, total earnings growth, and total dividend growth. Since Compustat has very sparse quarterly retained earnings data for our sample firms before 1972, we employ data only from 1972q1 to 2014q4 in generating the Table 9. Lastly, we also require all existing firms have non-missing observations for total earnings, total retained earnings, and total dividends to mitigate sample selection bias. The total observations are 89,599.

Following the same methods as used in both Table 7 and Table 8, we report average expected first and second moments of total earnings growth, total retained earnings growth, and total dividend growth for the 5 value-weighted portfolios that sorted based on consumption volatility risk loadings. Similarly, we perform time-series regressions within every portfolio. All three variables' (earnings, dividends, and retained earnings) expected first and second moments are regressed on corresponding expected consumption growth moments, respectively.

In the robustness checks of Table 9, we confirm our main finding that the cross-sectional difference in the dividend growth loadings on consumption volatility risk has an opposite direction compared that of earnings growth. In the Panel A, the covariance between

[12] We create monthly total dividend as the product of the dividend per share (divamt) and the number of share outstand (shrout), and every firm's total dividends are summed up within every quarter.

earnings growth volatility and the consumption growth volatility is negative in the Low β_σ portfolio, and it gradually increases from -4.76% to 0.30% in the High β_σ portfolio. The cross-sectional difference is 5.1% and statistically significant at 1%. On the other hand, in the Panel B, the sensitivity between total dividend growth volatility and the consumption growth volatility decreases from 1.08% in the Low β_σ portfolio to -0.29% in the High β_σ portfolio. The cross-sectional difference is -1.40% and statistically significant at 1%. The patterns for dividend growth and earnings growth that have appeared in our Table 7 and Table 8 are still the same in our Table 9. Therefore, we once again show that the negative risk premium for consumption volatility risk is explained by both dividend and earnings. Furthermore, in the Panel C, the covariance between retained earnings growth volatility and the consumption growth volatility decreases from 0.28% to -0.09%, and the cross-sectional difference is -0.37% and statistically significant at a 95% confidence level. Although both dividend growth volatility and retained earnings growth volatility have the same decreasing coefficient pattern across quintiles when regressed against consumption growth volatility, the decreasing trend is flatter in the retained earnings growth. This might be because retained earnings are affected by both earnings and dividends.

Table 9: Total Earnings, Total Dividends, and Total Retained Earnings[13]

We report the average expected first and second moments of total earnings growth, total dividend growth, and total retained earnings growth for the 5 value-weighted portfolios that are sorted based on consumption volatility risk loadings. Also, their sensitivities to expected first and second moments of consumption growth are reported. Time-series regressions are measured within each portfolio. The sample time range is between 1972q1 and 2014q4.

$$\mu_{i,t}^{ibq} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^{ibq} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

[13] The cross-sectional differences in sensitivity between adjacent portfolios are statistically significant except the difference between first quintile and second quintile in Panel B.

Panel A: Total earnings growth before extraordinary items (ibq)						
	Low β_σ		Med β_σ		High β_σ	High-Low
Mean (%)	9.45	6.44	6.26	4.77	3.95	-5.50
Std. Dev (%)	3.52	2.55	1.21	1.55	1.21	-2.31
$\emptyset_\mu$	-0.0181***	-0.00722***	-0.00774***	0.00894***	-0.00718***	0.0109**
	(-3.42)	(-3.06)	(-6.95)	(4.58)	(-5.46)	(1.99)
$\emptyset_\sigma$	-0.0476***	-0.0265***	-0.0149***	0.000590	0.00295***	0.0505***
	(-7.77)	(-6.07)	(-9.09)	(0.45)	(4.74)	(8.15)

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

$$\mu_{i,t}^d = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^d = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

Panel B: Total dividend growth (td)						
	Low β_σ		Med β_σ		High β_σ	High-Low
Mean (%)	8.74	6.96	6.20	5.45	4.55	-4.19
Std. Dev (%)	3.18	2.30	1.39	2.49	2.59	-0.59
$\emptyset_\mu$	0.0145**	0.00702***	-0.00347**	0.0104***	-0.00930**	-0.0238***
	(2.36)	(2.66)	(-2.31)	(2.96)	(-2.59)	(-2.93)
$\emptyset_\sigma$	0.0108**	0.00730***	-0.00281**	0.00150	-0.00292**	-0.0137***
	(2.40)	(3.75)	(-2.10)	(0.81)	(-2.05)	(-2.84)

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

$$\mu_{i,t}^{req} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t;\;\; \sigma_{i,t}^{req} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

Panel C: Total retained earnings growth (req)						
	Low β_σ		Med β_σ		High β_σ	High-Low
Mean (%)	6.50	6.00	5.66	5.58	3.71	-2.79
Std. Dev (%)	1.57	3.19	1.52	0.96	0.38	-1.19
$\emptyset_\mu$	-0.000127	0.0191***	-0.000534	0.0360***	0.00414***	0.00427
	(-0.05)	(5.01)	(-0.20)	(5.07)	(6.20)	(1.61)
$\emptyset_\mu$	0.00281**	0.0102***	0.000100	0.00813***	-0.000851***	-0.00366**
	(1.99)	(3.30)	(0.03)	(3.18)	(-2.88)	(-2.51)

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 10 presents empirical evidence of the direct connection between dividend and earnings. Lamont (1998) documents that the dividend payout ratio predicts future returns because both dividend and earnings have effects on future return. Motivated by the findings of Lamont (1998), we again use the methodology of BK to test the relationship between payout ratio and consumption.

Using same sample as created for Table 9, we first calculate the dividend payout ratio as total dividend divided by total earnings. We follow the same steps used previously, such as 1) creating value-weighted payout ratio; 2) converting the payout ratio to real value; 3) generating the quarterly payout ratio growth; 4) smoothing the payout ratio growth; 5) performing Markov switching process and obtain expected first and second moments of the payout ratio growth; and 6) regressing the payout ratio growth moments on the respective consumption growth moments.

As shown in the last row of our Table 10, the sensitivity between the payout ratio growth volatility and the consumption growth volatility decreases as the consumption risk increases, which is the same pattern as for dividends in the Table 7 and Table 9. Moreover, there is statistical significance at the 95% confidence level for the negative cross-sectional difference in the dividend payout ratio growth loadings on the consumption growth volatility (High-Low). The intuition behind the empirical results of the Table 10 is that investors require less risk premium for firms whose dividend payout ratio volatility has with less covariance with consumption risk. That is to say, expected return is lower for stocks with a stable payout ratio.

Table 10: Payout ratio

The top two rows of the table report descriptive statistics of average expected first and second moments of payout ratio growth for the 5 value-weighted portfolios that are sorted based on consumption volatility risk loadings. The lower rows show sensitivities of the payout moments to expected first and second moments of consumption growth. Time-series regressions are measured within each portfolio. The sample time period is between 1972q1 and 2014q4.

$$\mu_{i,t}^{pr} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^{pr} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

Payout Ratio Growth (pr)						
	Low β_{σ}		Med β_{σ}		High β_{σ}	High-Low
Mean (%)	9.63	10.41	10.51	3.08	-2.56	-12.20
Std. Dev (%)	2.74	5.59	3.68	0.59	5.77	3.02
$\emptyset_{\mu}$	-0.0112	0.00150	-0.0367***	-0.00767***	0.0800***	0.0912***
	(-1.20)	(0.19)	(-6.84)	(-4.54)	(5.96)	(4.28)
$\emptyset_{\mu}$	-0.0333***	-0.0405***	-0.0248***	-0.00471***	-0.0578***	-0.0244**
	(-5.34)	(-7.74)	(-6.53)	(-5.31)	(-4.07)	(-2.34)

t statistics in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

The results of Table 10 are important because they demonstrate that the effects of dividends and earnings are not independent of each other; rather, these effects are conjoined and concurrent.

The concurrent but opposite relationships of dividends and earnings growth volatility with respect to consumption growth volatility offer some explanation as to why observed stock returns are much more volatile than consumption or dividends, as the volatility of earnings is greater than that of either consumption or dividends. Overall, our results demonstrate that both dividends and earnings have significant influence on the expected return of investors.

2.4 Future Research

One possible direction for our future research is earnings quality. Lamont (1998) states that earnings have predictive power for future return because they are a measure of business condition. As shown in our Table 8 and Table 9, earnings growth volatility and consumption growth volatility are positively related in the fifth portfolio but negatively related in the first portfolio. Given the positive correlation between earnings, consumption and the economic cycle, firms which are classified in the last quintile have earnings that grow in step with the economy, whereas firms in the first quintile have lower earnings growth during economic expansion. We predict that earnings quality will be highest for firms whose earnings growth mirrors economic growth.

Moreover, Yee (2006) mathematically links earnings with the consumption capital asset pricing model (CCAPM), thereby showing that high earnings quality reduces the cost of capital. Since our sample indicates that the cost of capital for the fifth portfolio is lower than that for the first portfolio, the inference is that earnings quality of firms in portfolio 5 will be higher than the earnings quality of firms that in the portfolio 1. Our future may use earnings quality proxies that are presented in Dechow, Ge, and Schrand (2010) to prove our hypotheses.

Chapter 3 Conclusion

In this paper, we examine how dividends and earnings act on expected return in relation to aggregate consumption. Consumption literature typically uses dividends as the underlying mechanism connecting aggregate consumption and expected return. The problem is that the time series data for both dividends and consumption are much too smooth to explain observed stock returns, a phenomenon known as the equity premium puzzle. In the hunt to explain returns, Lamont (1998) jointly tests dividends and earnings and finds that both are significant explanatory variables for predicting return. But later, using similar direct bivariate regressions, Ang and Bekaert (2007) find that the results of Lamont (1998) for earnings do not hold when a longer time period is used. In this paper, our results strongly support Lamont (1998), even over longer time periods; our methodology is quite different from Ang and Bekaert (2007) because we follow the consumption driven approach of BK and use portfolios sorted by risk loading of expected return on consumption risk.

We first confirm the result of BK showing decreasing expected portfolio return across quintile portfolios sorted on increasing risk loading of expected return on consumption growth volatility risk, indicating a negative risk premium. Using the same portfolios sorted on risk loading, coefficients of expected dividend growth volatility regressed against expected consumption growth show a similar decreasing pattern. Hence, dividend cash flows provide an explanation for the negative pricing of risk shown across the portfolio risk loadings; the intuition is that stocks with a higher price of risk have lower expected return because they have lower sensitivity of dividend growth volatility to consumption volatility risk.

Motivated by the findings of Lamont (1998), we go further and also look at earnings growth across the risk loading portfolios, and find an opposite pattern of increasing coefficients when expected earnings growth volatility is regressed against expected consumption growth volatility. Furthermore, to demonstrate that dividends and earnings have a conjoined effect on expected return, we examine dividend payout ratio across the risk loading portfolios and find a pattern of decreasing coefficients for payout growth volatility regressed against consumption growth volatility risk, similar to dividends. Given that the economic cycle, consumption, and earnings are positively correlated, we attribute the different relationships of dividends and earnings to consumption as the consequence of dividends being the permanent component of earnings, while earnings contain a time varying component of retained earnings that is reinvested for future growth.

The quintile portfolio with the highest risk loading, meaning the highest price of consumption risk, has the lowest expected return, the lowest dividend growth volatility coefficient, the highest earnings growth volatility coefficient, and the lowest payout ratio volatility coefficient. The intuition of these results is that investors assign a low expected return to firms with a high price of consumption risk because those firms concurrently maintain stable dividend growth regardless of prevailing consumption growth risk, vary retained earnings reinvestment growth in step with consumption growth, and maintain a stable dividend payout ratio.

A puzzle in the results of BK is the statistical insignificance of the relationship between the first moment of dividend growth and the first moment of consumption growth, for which theory predicts a positive relationship. We confirm the lack of significance when the data period starts in 1946 as in BK, but we find that the relationship becomes significant when the data period starts in 1972. We speculate that the mixed results for the first moment analysis might arise from the unusually high economic growth rates in the 20 years following World War II; real GDP growth averaged nearly 4% in the 1950s, nearly 5% in the 1960s, compared with 2% to 3% thereafter. In contrast, our analysis for second moments is robust in all time periods.

The importance of our findings lies in showing that the mechanism by which consumption growth risk transmits to expected return is the conjoined effect of both dividends and earnings cash flows. This paper contributes to the literature that seeks to explain why asset prices are so much more volatile than consumption or dividends.

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Appendix:

We employ Equation 10 of Boguth and Kuehn (2013) in producing our Table 1.

$$\Delta c_{t+1} = \Delta s_{t+1} - \Delta v_{t+1} \text{ (10)}$$

- ΔC_{t+1}: log total consumption growth.
- ΔS_{t+1}: log service consumption growth.
- ΔV_{t+1}: changes in the log service consumption share.

We employ Equation 12 of Boguth and Kuehn (2013) in producing Table 2.

$$R_t^i - R_t^f = \alpha_t^i + \beta_{c,t}^i \Delta c_t + \beta_{\mu,t}^i \Delta\widehat{\mu_t} + \beta_{\sigma,t}^i \Delta\widehat{\sigma_t} + \varepsilon_t \text{ (12)}$$

- $(R_t^i - R_t^f)$: firm's quarterly excess return.
- (Δc_t): change in log consumption growth.
- $(\Delta\widehat{\mu_t})$: change in the first moment of consumption growth.
- $(\Delta\widehat{\sigma_t})$: change in the second moments of consumption growth.

Equation that employed in Table IX of Boguth and Kuehn (2013) is used in our Table 7 and Table 9.

$$\mu_{i,t}^d = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^d = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

- d stands for dividend that is a distribution of firm's assets to its shareholders.
- We use this equation with dividend per share in our Table 7 and with total dividends in our Table 9.
- $\mu_{i,t}^d$: first moment of dividend growth in each quintile.
- μ_t: first moment of consumption growth.
- $\sigma_{i,t}^d$: second moment of dividend growth in each quintile.
- σ_t: second moment of consumption growth.

Other Equations that employed in Chapter 2

$$\mu_{i,t}^{ibq} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^{ibq} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

- ibq: quarterly income before extraordinary items.
- We define the ibq as earnings which are exclusive for shareholders.
- $\mu_{i,t}^{ibq}$: first moment of earnings growth in each quintile.
- μ_t: first moment of consumption growth.
- $\sigma_{i,t}^{ibq}$: second moment of earnings growth in each quintile.
- σ_t: second moment of consumption growth.

$$\mu_{i,t}^{req} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^{req} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

- req: quarterly retained earnings.
- Retained earnings are a portion of earnings that leftover after dividends paid to shareholders.
- $\mu_{i,t}^{req}$: first moment of retained earnings growth in each quintile.
- μ_t: first moment of consumption growth.
- $\sigma_{i,t}^{req}$: second moment of retained earnings growth in each quintile.
- σ_t: second moment of consumption growth.

$$\mu_{i,t}^{pr} = \tau_{\mu,i} + \emptyset_{\mu,i}\mu_t; \;\; \sigma_{i,t}^{pr} = \tau_{\sigma,i} + \emptyset_{\sigma,i}\sigma_t$$

- pr: quarterly payout ratio.
- Payout ratio is equal to dividends divided by earnings.
- $\mu_{i,t}^{pr}$: first moment of payout ratio growth in each quintile.
- μ_t: first moment of consumption growth.
- $\sigma_{i,t}^{pr}$: second moment of payout ratio growth in each quintile.

- σ_t: second moment of consumption growth.