Heterogeneous Cash-Flow Risk and the Cross Section of Return Correlations

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Abstract

Heterogeneous cash-flow risk affects the cross section of stock returns. Assets with a low covariance of cash-flow and consumption growth can serve as natural hedges against negative shocks in the economy. I find that stocks with high cash-flow risk have higher excess returns and a higher degree of asymmetric dependence, i.e. a higher correlation of stock returns with market returns during downturns relative to upturns. I use a consumption-based asset-pricing model with heterogeneous habits to make predictions about the effects of the firm-level cash-flow risk on the cross section of returns and return correlations. These predictions are largely confirmed by data.

Keywords: heterogeneous cash-flow risk, asset pricing, state-dependent return correlations

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1. Introduction

Correlations between stock returns seem to be related with the business cycle and exhibit asymmetric dependence. Asymmetric Dependence (AD) describes a situation when the dependence between a stock and the market differs during market downturns from that during market upturns (Patton, 2004). Many authors provide empirical evidence of a higher correlation of stock returns with market returns during bad times relative to good times (Chabi-Yo, Ruenzi, and Weigert, 2017; Weigert, 2015; Kelly and Jiang, 2014; Ang, Hodrick, Xing, and Zhang, 2006; Hartmann, Straetmans, and De Vries, 2004; Patton, 2004; Ang and Bekaert, 2002; Ang and Chen, 2002; Campbell, Koedijk, and Kofman, 2002; Longin and Solnik, 2001; Knight, Satchell, and Tran, 1995). Alcock and Hatherley (2016) suggest that not all US listed equities are more correlated with the market in bad times relative to good times.

Despite many papers documenting the empirical evidence of asymmetric dependence between stock returns and market returns, it still remains unclear why AD exists. I contribute to the existing literature by identifying potential drivers, that may help us understand why certain stocks (or portfolios of stocks) exhibit different degrees of asymmetric dependence, that is namely the lower-tail and the upper-tail asymmetric dependence, see Figure 1 for further description.

[FIGURE 1 AROUND HERE]

The identification of assets with a low correlation in bad states (diversification) and a high correlation in good states (abnormal gains) is very attractive for investors. Alcock and Hatherley (2016) show that a relatively high (low) return correlation of stock returns with market returns in bad times relative to good times is associated with a significant return premium (discount). Their paper, however, does not explain why certain stocks are performing relatively worse or better than other during market downturns.

Existing theory suggests that asset returns are negatively correlated with the business cycle, see e.g. Cochrane (2017); Ehling and Heyerdahl-Larsen (2017); Ehling, Gallmeyer, Heyerdahl-Larsen, and Illeditsch (2016); Menzly, Santos, and Veronesi (2004). Most asset-pricing models focus on an average stock (a single risky asset). As a result, the theoretical foundations of the variation in the cross section of return dependence remain largely under-researched.

I build on the note of Menzly et al. (2004) and Santos and Veronesi (2016) and propose a model with consumers having heterogeneous habits and firms with heterogeneous cash-flow risk. Menzly et al. (2004) suggest that the sign of the covariance of the stock's dividend growth with consumption growth determines whether a risky asset is a good or a bad hedge against negative consumption shocks. If the covariance is negative, the asset constitutes of a larger fraction of consumption when consumption decreases and serves as a natural hedge against negative consumption shocks. As a result, stocks with a negative covariance are more likely to perform relatively better than other assets during market downturns.

This specific form of the model assumptions is convenient to capture the state dependence of asset prices and return correlations from the following reasons. First, I assume that the consumer's sensitivity to habit is high during market downturns relative the market downturns. Second, the level of habit depends on excess output of the economy at each period, which is expected to be low in bad time relative to good times. This is because negative consumption shocks decrease aggregate consumption, which further lowers excess output. Last, the firm-level heterogeneous cash-flow risk interacts with

This theoretical model provides possible explanations for the variations in the cross-sectional return correlations. The model suggests that stocks with a low cash-flow risk, i.e. the covariance between growth in firm cash flows and consumption, are more likely to exhibit return correlations (with other stock returns and the market) that are relatively low during bad times compared to good times. Moreover, the model implies that heterogeneous cash-flow risk is priced in the cross section of stock returns as expected excess returns are also affected by the firm-level cash-flow risk.

I contribute to the existing literature by empirically testing the main theoretical arguments related to cash-flow risk using novel proxies of cash flows and consumption. I show that heterogeneous cash-flow risk does not only affect stock return correlations but is also priced in the cross section of stock returns. I use the unfiltered consumption data (Kroencke, 2017), which allows me to capture the time-variation in asset prices. In contrast to Menzly et al. (2004), I do not focus on dividends only but account for all sources of cash flows using the net payout, as suggested by Larrain and Yogo (2008).

I find that heterogeneous cash-flow risk affects the cross section of stock returns. US listed stocks with high cash-flow risk have higher excess returns and higher degree of lower-tail asymmetric dependence. The main model predictions about the effect of cash-flow risk on expected returns are confirmed empirically.

My findings suggest that assets with a high covariance of cash-flow and consumption growth will perform relatively poorly during market downturns as they will experience abnormal losses driven by the asymmetric dependence of stock returns.

This paper relates to literature on consumption-based asset-pricing with external habit formation (Campbell and Cochrane, 1999), heterogeneous habits (Santos and Veronesi, 2016) and the existence of heterogeneous asymmetric dependence (Alcock and Hatherley, 2016). This paper is also related to Ehling et al. (2016), who are the first to study correlations using a consumption-based theory. I extend this framework by focusing on the cross-sectional variations in the state dependence of return correlations.

The structure of this paper is the following. Section 2 describes the theoretical model, Section 3 discusses the data used and Section 3.4 provides further details about the importance of cash-flow risk for asset prices. In Section 4, I provide the empirical results testing the theoretical implications and conclude in Section 5.

2. The Model

2.1. Consumers

Consumers derive utility from individual consumption and external habit. The consumers' utility function is the same as in Santos and Veronesi (2016). The model differs from Santos and Veronesi (2016) by assuming that there are N risky assets with heterogeneous cash-flow risk, as described later in the section.

$$U(C_t^i, X_t^i) = E_t\left[\int_0^\infty e^{-\rho(\tau-t)} u_j(C_t^i, X_t^i)dt\right], \tag{1}$$

where $\rho > 0$ is the subjective discount rate, C_t^i is the consumer i's consumption rate at time t, X_t^i is the external habit of consumer i at time t and u is the individual instantaneous utility function defined as

$$u\left(C_t^i, X_t^i\right) = \log(C_t^i - X_t^i). \tag{2}$$

Consumers have heterogeneous habits (Santos and Veronesi, 2016):

$$X_t^i = g_t^i\left(C_t - \bar{X}_t\right), \tag{3}$$

where C_t is the aggregate consumption at time t, $\bar{X}_t$ is the average habit, $\bar{X}_t = \int X_t^l dl$, and g_t^i is consumer i's sensitivity to excess output of the economy at time t, i.e. the difference between aggregate consumption C_t and average habit $\bar{X}_t$. The aggregate consumption dynamics are

$$\frac{dC_t}{C_t} = \mu_C dt + \sigma_C dZ_t, \tag{4}$$

where μ_C is a constant drift term, Z_t is a Brownian motion (vector) and σ_C is the constant volatility of the aggregate consumption.

The sensitivity of individual habits to excess output is a function of the state variable Y_t.

$$g_t^i = \frac{1}{a_i}C_t + b_i \tag{5}$$

The inverse surplus ratio (Menzly et al., 2004), Y_t, is given as

$$Y_t = \frac{1}{S_t} = \frac{C_t}{C_t - \bar{X}_t}, \tag{6}$$

where S_t is the surplus ratio.

The dynamics of the surplus ratio are crucial for determining the variations in asset prices. I follow Campbell and Cochrane (1999) and Menzly et al. (2004) and assume that $\log(S_t)$ is a mean-reverting process with shocks correlated with innovations in consumption growth.

The dynamics of the inverse surplus ratio are

$$dY_t = k(\bar{Y} - Y_t)dt - \alpha(Y_t - \lambda)Y_t \left[\frac{dC_t}{C_t} - \mu_C dt\right], \tag{7}$$

where k is the speed of mean reversion and $\bar{Y}$ is the long run mean of the inverse surplus ratio. Parameters α and λ described the effects of unexpected consumption shocks on the inverse surplus ratio. Menzly et al. (2004) specify the parameter α to be positive ($\alpha > 0$), which means that with a negative aggregate shock to economy, the inverse surplus ratio increases, and vice versa. The inverse surplus ratio thus represents a recession indicator; it has a high (low) value during market downturns (upturns). The parameter λ is restricted ($\lambda \geq 1$), which applies a lower bound on the inverse surplus ratio.

Table 1 describes the state dependence of the model parameters and variables.

Table 1: State Dependence of the Consumption-based asset pricing model.

	Bad Times	Good Times
Consumer Sensitivity to Habit (g_{it})	$\uparrow$	$\downarrow$
Excess Output ($C_t - \bar{X}_t$)	$\uparrow$	$\downarrow$
Habit Level (X_{it})	$\uparrow$	$\downarrow$
Consumption Shocks ($\frac{dC_t}{C_t} - \mu_c dt$)	< 0	> 0
Inverse Surplus Ratio (Y_t)	$\uparrow$	$\downarrow$

2.2. Assets

There are N risky assets and one risk-free asset in the economy. The risky assets pay dividends and form agents' aggregate output. Dividend share processes are stationary and mean-reverting. Instead of modelling the dividend rate processes, I focus on the share of output that each risky security produces (Menzly, Santos, and Veronesi, 2004),

$$s_t^j = \frac{D_t^j}{C_t}, \text{ for } j = 1, ..., N. \tag{8}$$

The consumption share of the risky asset j follows a continuous mean-reverting process.

$$ds_t^j = \phi^j(\bar{s}^j - s_t^j)dt + s_t^j \sigma^j(s_t) dZ_t, \tag{9}$$

where $\sigma^j(s_t) = (\sigma(s^1), ..., \sigma(s^N))$ is a vector of volatilities,

$$\sigma^j(s_t) = v_i - \sum_{k=1}^{N} s_k(t) v_k, \tag{10}$$

ϕ^j is the speed of mean reversion of the share process j, v_i denotes a vector of constants, $v_i = (v_i^1, ..., v_i^N)$ and Z_t is a vector of Brownian motions. I follow Menzly et al. (2004) and normalize the constants v_i to satisfy $\sum_{k=1}^{N} \bar{s}_k v_k = 0$, which does not change the share process but simplifies the analytical solution.

Heterogeneous Cash-Flow Risk

I assume that risky assets have heterogeneous cash-flow risk (Menzly et al., 2004), which is defined as the covariance between the share of dividend output each asset produced (s_t^j) and the aggregate consumption (C_t). The covariance between the the consumption share of the risky asset j and consumption growth is given by

$$\text{cov}_t \left(\frac{ds_t^j}{s_t^j}, \frac{dC_t}{C_t} \right) = \theta_{CF}^j - \sum_{l=1}^{N} \theta_{CF}^l s_t^l. \tag{11}$$

The volatility constants v from equation (10) are normalized so that the expected value of $\sum_{l=1}^{N} \theta_{CF}^l s_t^l$ is equal to zero and $\text{E}_t \left(\text{cov}_t \left(\frac{ds_t^j}{s_t^j}, \frac{dC_t}{C_t} \right) \right) = \theta_{CF}^j$.

2.3. Asset Returns

The price of the risky asset j is the expected value of future dividend income

$$P_t^j = \mathrm{E}_t \left[\int_t^\infty e^{-\rho(\tau - t)} D_\tau^j d\tau \right]. \tag{12}$$

This can be arranged into

$$P_t^j = C_t \int_t^\infty e^{-\rho(\tau - t)} \ \mathrm{E}_t \left(s_\tau^j \right) d\tau. \tag{13}$$

Applying Ito's lemma to equation (13) yields

$$\frac{dP_t^j}{P_t^j} = \left[\mu_C - \rho + \phi^j \frac{\bar{s}^j - s_t^j}{s_t^j} - \sigma^j(s_t)\sigma_C \right] dt + \left[\sigma_C + \sigma^j(s_t) \right] dZ_t, \tag{14}$$

where $\mathrm{E}_t(\sigma^j(s_t)\sigma_C) = \theta_{CF}^j + \sigma_C^2$. This suggests that the price dynamics of the risky asset j are positively related with cash-flow risk (θ_{CF}^j).

The risk-free rate is given by

$$r_t = \rho + \mu_C - (1 - \alpha(Y_t - \lambda))\sigma_C^2 + k(1 - \bar{Y}/Y_t).^2 \tag{15}$$

Excess returns of risky asset j (R_t^j) and return correlations ($\rho_t^{j,k}$) are affected by heterogeneous cash-flow risk (θ_{CF}^j) in the following manner. The excess return on asset j is defined as.

$$R_t^j = \frac{dP_t^j + D_t^j dt}{P_t^j} - r_t \tag{16}$$

Equations (14), (15) and (16) yield

$$\begin{aligned} R_t^j = & \left[\mu_C - \rho + \phi^j \frac{\bar{s}^j - s_t^j}{s_t^j} - \sigma^j(s_t)\sigma_C \right] dt + \left[\sigma_C + \sigma^j(s_t) \right] dZ_t \\ & + (P_t^j)^{-1} D_t^j dt - \left[\rho + \mu_C - (1 - \alpha(Y_t - \lambda))\sigma_C^2 + k(1 - \bar{Y}/Y_t) \right]. \end{aligned} \tag{17}$$

[2] The derivation of r_t is provided by Santos and Veronesi (2016), Proof of Proposition 3.

2.4. Asymmetric Return Correlations

Consider the correlation between excess returns on asset j (R_t^j) and the consumption growth

$$\rho_t^{j,C} = \frac{\mathrm{cov}_t\left(R_t^j, \frac{dC_t}{C_t}\right)}{\sigma(R_t^j)\sigma_C} \tag{18}$$

Next, compare return correlations in good states relative to bad states for different levels of exceedances. I examine the level of upper tail return correlation

$$\rho_t^+(\delta_i) = \rho_t(R^j, \frac{dC_t}{C_t}|dZ_t > \delta_i) \tag{19}$$

relative to lower tail return correlation

$$\rho_t^-(\delta_i) = \rho_t(R^j, \frac{dC_t}{C_t}||dZ_t < \delta_i), \tag{20}$$

where δ_i is some level of the shock to aggregate consumption dZ_t.

Asymmetric dependence between stock j's returns and consumption growth is defined as

$$AD_t^j = \mathrm{sgn}((\rho_t^+(\delta) - \rho_t^-(\delta))'1)\left[(\rho_t^+(\delta) - \rho_t^-(\delta))'(\rho_t^+(\delta) - \rho_t^-(\delta)\right], \tag{21}$$

where δ is a vector of exceedances, $\delta = (\delta_1, ..., \delta_M)$. A negative (positive) value of AD_t^j corresponds to lower-tail (upper-tail) asymmetric dependence (Alcock and Hatherley, 2016), which is a situation where the correlation between the risky asset j and the consumption growth is higher (lower) in the lower tail relative to upper tail.

I am interested in studying the relation between the firm-level of asymmetric dependence (AD_t^j) and the firm-level cash flow risk (θ_{CF}^j).

$$\frac{\partial AD_t^j(\lambda^j)}{\partial \theta_{CF}^j} \tag{22}$$

This relation is examined in Section 4 using simulations from the model and observed data from the US equity market.

3. Data

3.1. Security Data

I use data on US listed firms from the WRDS CRSP-Compustat Merged database between 1960 and 2016. I limit my attention to firms listed on NYSE, Nasdaq and Amex (share code 1, 2 or 3). I collect monthly information about the firm identifier ('permno'), total stock return ('ret'), close price ('prc') and number of shares outstanding ('shrout') from the WRDS CRSP Monthly Security File. I retrieve information on the monthly market return and risk-free rate from the WRDS Fama-French Database.

3.2. Unfiltered Consumption

I use the unfiltered consumption, as proposed by Kroencke (2017), as a proxy for consumption. The filtered consumption is calculated using the price indexes for personal consumption for nondurable goods and services and is publicly available in the National Income and Product Accounts (NIPA) published by the Bureau of Economic Analysis. The NIPA consumption is smoothed to account for measurement error. As a result, it cannot by construction account for a large amount of time variations that is needed to explain asset prices.

Kroencke (2017) applies a filtering process to reverse the filtering contained in NIPA consumption. He introduces a filter to correct for the time-aggregation bias inherent in consumption bias. The filter is calibrated using simulation data. The unfiltered consumption growth used in this paper is collected from Tim Kroencke's personal website.[3]

[FIGURE 2 AROUND HERE]

Figure 2 demonstrates the effect of the Kroencke (2017)'s unfiltering procedure. The unfiltered consumption growth exhibits a significantly larger amount of time

[3]Downloaded from https://sites.google.com/site/kroencketim/data-programs on January 9, 2018.

variation relative to the original time series of NIPA consumption growth. For further details about the unfiltering procedure, see Kroencke (2017).

3.3. Cash Flows

Cash-flow data comes from from the WRDS Compustat Fundamental Annual File. I define cash flows consistent with Larrain and Yogo (2008). Larrain and Yogo (2008) suggest that the appropriate measure of cash flows is the net payout, because it accounts for all cash-flow items, i.e. dividends, interest, net repurchases of equity and debt.

I use the net payout to market asset value ratio as a proxy for cash flows. I follow the procedure described in Larrain and Yogo (2008) to collect data from Compustat to estimate net payout (NP) and market value of assets (MVA).

$$NP = Div + Eq\_Rep + LTD\_Rep + \max(-Debt\_Net, 0), \tag{23}$$

where Div are Cash Dividends, Eq_Rep are Purchases of Common and Preferred Stock, LTD_Rep is the Reduction in Long-Term Debt and $Debt\_Net$ are Changes in Current Debt.

[FIGURE 3 AROUND HERE]

MVA is the sum of the market value of equity (ordinary and preferred), long-term debt and and other liabilities. The market value of ordinary equity is the product of price per share and number of shares outstanding. The market value of preferred stock is calculated using the price of preferred share divided by Moody's medium-grade preferred dividend yield at the end of calendar year (Larrain and Yogo, 2008). Other liabilities include Total Current Liabilities, Other Liabilities, Deferred Taxes and Investment Tax Credit and Minority Interest. Table 2 provides a descriptive summary of the cash-flow items.

[TABLE 2 AROUND HERE]

Figure 3 displays the time-series development of the annual percentage change in NP, MVA and the average stock return. The NP growth is strongly related with the average stock return, which suggests that changes in stock returns are affected by cash-flow dynamics.

3.4. Heterogeneous Cash-Flow Risk

Menzly et al. (2004) suggest that heterogeneous cash-flow risk accounts for a large part of cross-sectional asset-pricing differences. The cash-flow risk is defined as a covariance between cash-flow and consumption growth.

$$\mathrm{cov}_t\left(\frac{ds_i(t)}{s_i(t)}, \frac{dC_t}{C_t}\right) \tag{24}$$

The sign of the covariance determines whether the asset is a good or a bad hedge against negative consumption shocks. If the covariance is negative, the asset constitutes of a larger fraction of consumption when consumption decreases and serves as a hedge against bad times.

Larrain and Yogo (2008) find that the variations in the firm net payout yield, e.g. the ratio of net payout to asset value, can be explained by movements in expected cash flow growth, instead of movements in discount rates. Their finding points out that variations in cash flows are important for expected asset prices.

[FIGURE 4 AROUND HERE]

I find that there are significant differences in firm cash-flow risk, Figure 4. This histogram shows the distribution of the firm-level covariances between net payout yield and consumption growth. A relatively high proportion of firms have a negative cash-flow / consumption growth covariance, which suggests that the their net payout yield increases when there is a negative consumption shock in the economy.

4. Empirical Tests (Preliminary Results)

4.1. Model Calibration

I simulate from the model described in Section 2 with parameters estimated using US data between 1960 and 2014. I assume that the mean consumption growth rate is 1% p.a and annual volatility is 2%. This assumption is consistent with observed data (unfiltered NIPA conusmption (Kroencke, 2017)). Figure 5 shows that deviation from these values leads to under or over-estimated aggregate consumption values.

[FIGURE 5 AROUND HERE]

I first estimate cash-flow risk (θ_{CF}) for all US listed equities using all data available for each stock. Next, I sort stocks into deciles based on the level of cash-flow risk. For each decile j (i.e. for a portfolio of all stocks in decile j), I calculate the consumption share of the decile (s_t^j), the volatility of the consumption share ($\sigma^j(s_t)$, its mean reversion coefficient (ϕ^j) and the long-term mean ($\bar{s}^j$). The estimated parameters are reported in Table 4. The remaining model parameters are chosen to be consistent with Menzly et al. (2004), Table 1.

[TABLE 4 AROUND HERE]

The simulated returns on risky assets are affected by firm-level cash-flow risk, Figures 6 and 7. The returns on stocks with the highest cash-flow risk (Decile 1) is greater than returns on stocks with the lowest cash-flow risk (Decile 10).

[FIGURE 6 AROUND HERE]

[FIGURE 7 AROUND HERE]

The simulated relation between the firm-level cash-flow risk and asymmetric dependence of stock returns is not linear, Figure 8. Stocks with the highest cash-flow risk (Decile 1) have relatively higher degree of lower-tail asymmetric dependence than stocks with the lowest cash-flow risk (Decile 10). Stocks with a zero cash-flow risk, however, have relatively high returns.

[FIGURE 8 AROUND HERE]

4.2. Observed Data

I verify whether the theoretical implications described in Section 2 hold empirically. I focus on the relation between the firm-level cash-flow risk and the cross section of stock returns, conditional asset prices and the asymmetric dependence of stock returns.

First, I test the theoretical implication that firms with a high cash-flow risk, i.e. the $\text{cov}_t\left(\frac{ds_i(t)}{s_i(t)}, \frac{dC_t}{C_t}\right)$, have a relatively higher excess return. Figure 9 shows the values of firm excess returns and risk-adjusted excess return (α)[4] sorted into cash-flow deciles. Stocks in decile 1 have the highest value of cash-flow risk.

[FIGURE 9 AROUND HERE]

Firms with high cash-flow risk have higher excess returns than stocks with low cash-flow risk. Nevertheless, this relation is not monotonous, deciles 5 and 6 break the monotonicity and have surprisingly high excess returns. The empirical results suggest that stocks with a covariance between cash-flow and consumption growth

[4]Risk-adjusted excess return (α) is estimated using the CAPM. It corresponds to the remaining excess return after subtracting the effect of market risk on firm excess returns. The estimation is in sample.

close to zero are some-what special. There may be other sources of risk affecting these stocks that may generate the unusually high excess returns.

[TABLE 3 AROUND HERE]

Table 3 provides further details on the cross section of stock returns, CAPM β, α when sorted into cash-flow risk deciles. I notice that stocks with the highest levels of cash-flow risk are more sensitive to market conditions, i.e. have a higher CAPM β.

Conditional Asset Prices

I have a particular interest in identifying characteristics of firms that perform relatively better during downturn periods. Therefore, I explore the conditional performance of stocks during market downturns and upturns. I examine conditional excess returns, net payout growth and market asset value growth, Table 5. I define market downturns (upturns) to be the months when the market excess return is negative (positive).

[TABLE 5 AROUND HERE]

Stocks with the lowest cash-flow risk (deciles 7-10 from Figure 10) experience a very similar net payout growth during market downturns and upturns. We can, therefore, consider these stocks to be relatively stable, as their cash-flows are not heavily affected by market conditions. With an increasing cash-flow risk (when moving from decile 6 to 1), the difference between the net payout growth during market upturns and downturns increases monotonically. Stocks with a higher degree of cash-flow risk (decile 1) experience a 7% higher net payout growth in good times relative to bad times. For stocks in decile 10 (the lowest cash-flow risk), this difference is only less than 2%, annually. This suggests that the net payout ratio of low cash-flow risk stocks is considerably less state-dependent, as compared to high cash-flow risk stocks.

[FIGURE 10 AROUND HERE]

Stocks with the lowest growth in market asset value are typically firms with a cash-flow risk close to zero. On the other hand, stocks with a very low or a very high cash-flow risk have a substantially higher market asset value growth (by up to 7% per annum).

Asymmetric Dependence of Stock Returns

I use the Alcock and Hatherley (2016) Adjusted-J statistic (J^{Adj}) to empirically measure the degree of state dependence of stock returns. This statistic is a convenient measure for the purpose of this paper because it can distinguish between the various types of state dependence, i.e. the lower-tail asymmetric dependence, upper-tail asymmetric dependence and symmetric dependence as illustrated graphically in Figure 1.

A negative (positive) value of the J^{Adj} refers to lower-tail (upper-tail) asymmetric dependence, which is a situation when stock returns are more correlated with market returns during market downturns (upturns) relative to market upturns (downturns). When J^{Adj} approaches zero, the return dependence structure is symmetric.

I find that stocks with the lowest cash-flow risk exhibit the lowest degree of lower-tail asymmetric dependence, Figure 11. The slope of the relation between the degree of asymmetric dependence and cash-flow risk is, however, not constant. The average level of asymmetric dependence is relatively flat in the first five deciles (i.e. stocks with relatively high cash-flow risk). The degree of asymmetric dependence then decreases (getting closer to zero) when moving from decile six to decile ten. This finding suggests that stocks with a low cash-flow risk are likely to experience a lower degree of lower-tail asymmetric dependence. These findings are consistent with the simulations from theoretical model described in Section 2, see Figure 8.

[FIGURE 11 AROUND HERE]

The average J^{Adj} is negative in all the cash-flow risk deciles. A negative value of J^{Adj} is associated with lower-tail asymmetric dependence of stock returns. This implies that sorting into deciles may not be sufficient to identify stocks exhibiting upper-tail asymmetric dependence. We must also note that there are not that many stocks that empirically exhibit upper-tail asymmetric dependence (only less than 15% of all stocks listed in the US). The identification of such stocks is thus a complicated task.

[TABLE 6 AROUND HERE]

Overall, the empirical results confirm that the cross section of return correlations is related with heterogeneous cash-flow risk. Further exploration is, however, required to progress with the identification of assets that exhibit upper-tail asymmetric dependence as sorting into deciles was not sufficient.

5. Conclusion

The firm-level cash-flow risk is an important driver of firm excess returns and their asymmetric dependence characteristics. In this paper, I make theoretical asset-pricing arguments using a consumption-based model with heterogeneous habit formation and heterogeneous cash-flow risk.

The theory suggests that with a negative consumption shock, assets with a low cash-flow risk will perform relatively better. The model predictions are largely confirmed by empirical observations. Nevertheless, the empirical exploration is done in sample based on sorting into cash-flow risk deciles, which requires further attention. These results are, therefore, preliminary. It requires more advanced out-of-sample tests, which will be added to the next version of this paper.

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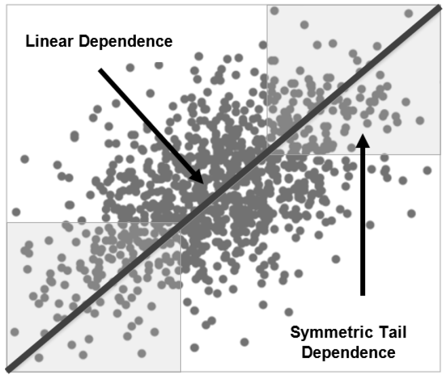
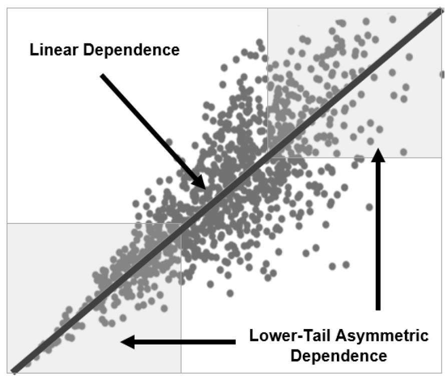
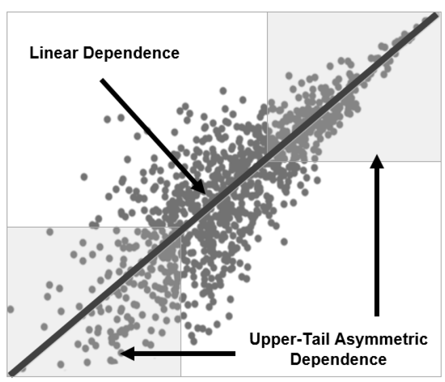
Types of Return Dependence



(a) Symmetric Dependence



(b) Lower-Tail Asymmetric Dependence (LTAD)



(c) Upper-Tail Asymmetric Dependence (UTAD)

Figure 1: Scatter plot of simulated bivariate data with different types of dependence. The dependence between stock excess returns and market excess returns may be described by a linear component (CAPM β) and a higher-order components, capturing differences in dependence across the joint return distribution. A joint distribution that displays larger dependence in one tail compared to the opposite tail is said to display asymmetric dependence. Panels (1a) to (1c) display three possible types of return dependence, symmetric dependence, lower-tail asymmetric dependence and upper-tail asymmetric dependence.

NIPA Consumption: annual growth (%)

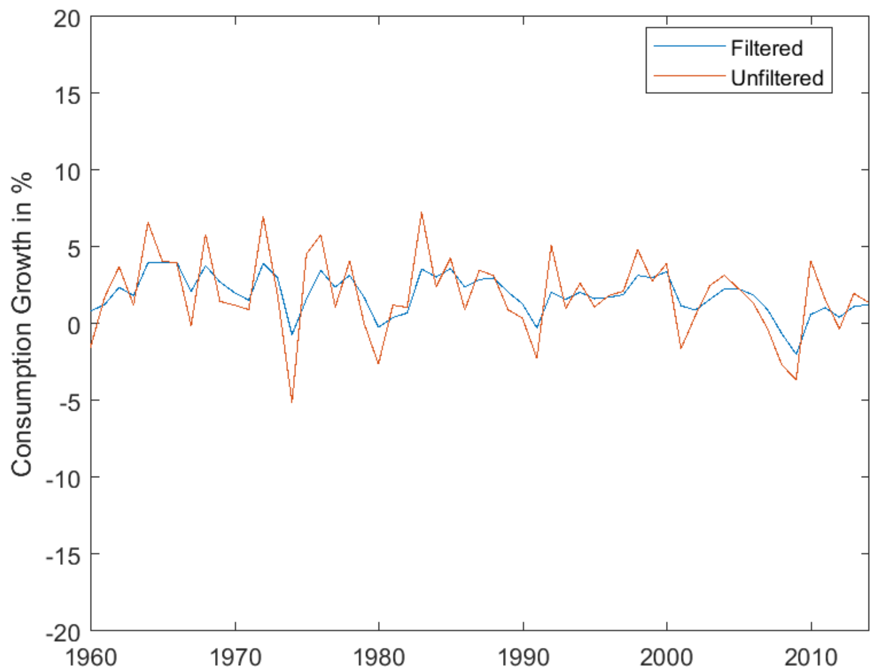


Figure 2: National Income and Product Accounts (NIPA) Consumption Growth (1960-2014). Both unfiltered and filtered consumption growth is from Kroencke (2017). The filtered consumption growth is calculated using the price indexes for personal consumption for nondurable goods and services, issued by Bureau of Economic Analysis. Information about the unfiltering procedure is available in Kroencke (2017). Both unfiltered and filtered consumption growth is downloaded from https://sites.google.com/site/kroencketim/data-programs on January 13, 2018.

Cash Flows: annual growth (%)

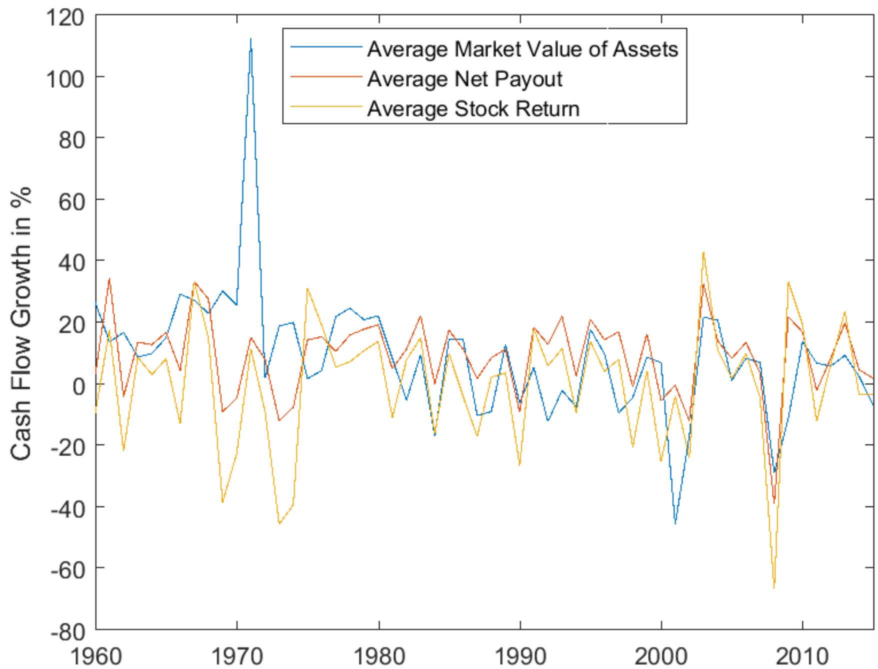


Figure 3: This plot describes the average annual growth of the market value of assets (MVA), net payout (NP) and average stock return of US listed firms between 1960 and 2015. Cash-flow data comes from Compustat Fundamental Annual database. The estimation of MVA and NP is described in Section 3.3. All US listed stocks are considered (1960-2016).

The Cross Section of Firm Cash-Flow Risk

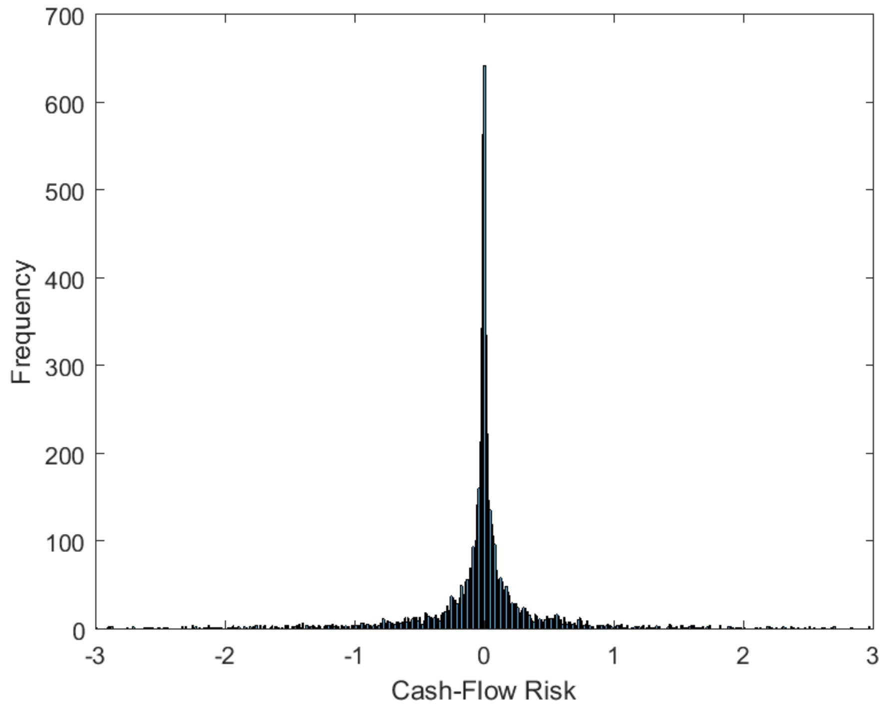


Figure 4: Histogram of the cross section of firm cash-risk. The cash-flow risk is defined in Section 3.4 as the covariance of firm cash-flow growth and consumption growth. The ration of net payout to market value of assets is used as a proxy of cash-flow growth. The unfiltered consumption (Kroencke, 2017) is used to explain time-series variation in asset prices. All US listed stocks are considered (1960-2016).

Aggregate Consumption Process: Simulated vs Observed (Annual)

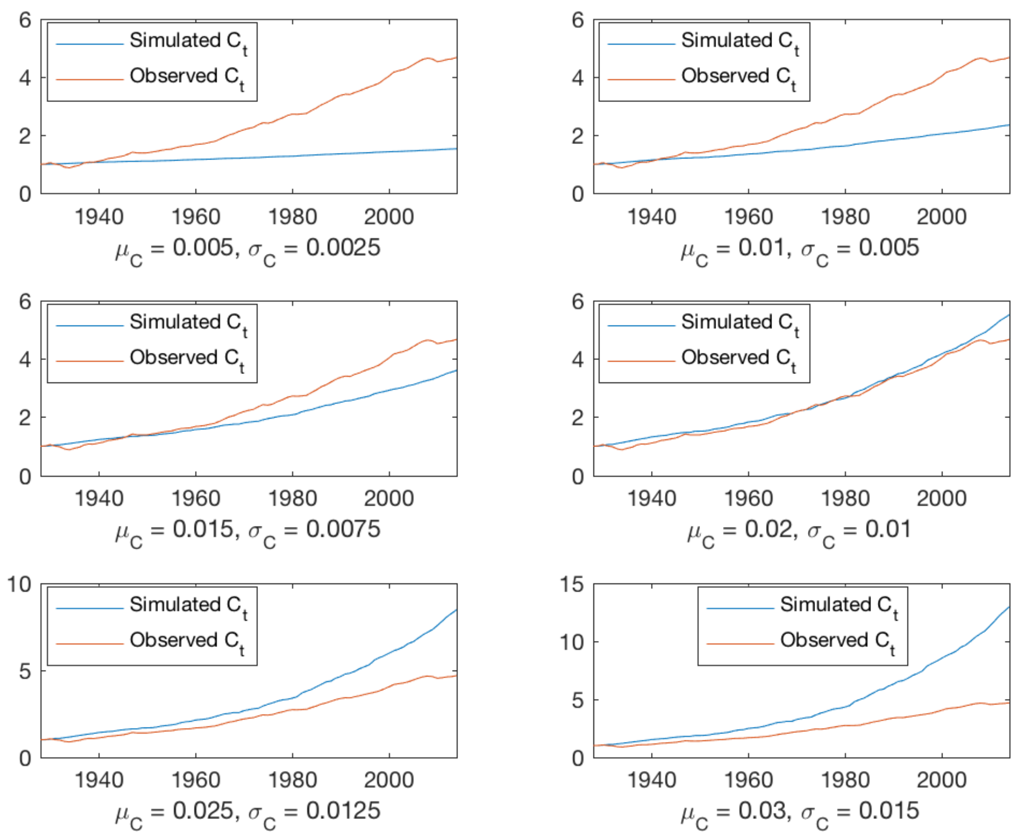


Figure 5: Choice of Model Parameters. Sensitivity Analysis. This figure shows the effect of changing the input parameters μ_C and σ_C. The blue line corresponds to the simulated path of the aggregate consumption and the red line represents the observed aggregate consumption, calculated based on the unfiltered consumption growth (Kroencke, 2017) using NIPA Consumption Growth data from 1929 to 2014) . We choose parameters $\mu_C = 0.02$ and σ_C because it fits the observed data the best and is consistent with Menzly et al. (2004) and Santos and Veronesi (2016).

Cash-Flow Risk and Returns of Risky Assets: Simulated (Annual)

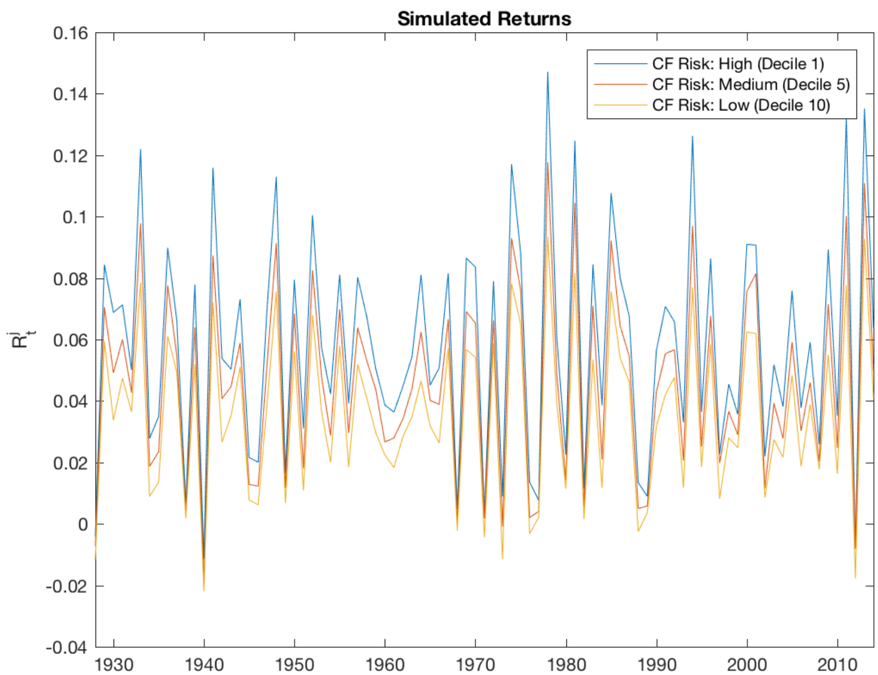


Figure 6: This figure shows the time development of the returns on risky assets with different levels of cash-flow risk. Model parameters are described in Table 4. The parameters are estimated using US data between 1960 and 2014. US stocks are sorted into deciles based on their cash-flow risk (θ^j_{CF}). Decile 1 (10) consists of stocks with the highest (lowest) cash-flow risk.

Simulated Stock Returns vs Cash-Flow Risk

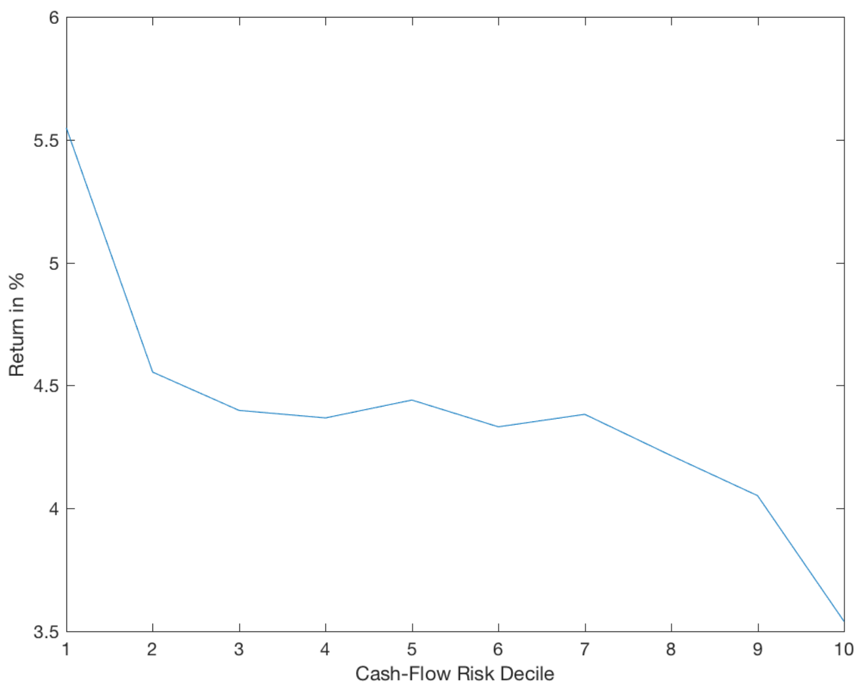


Figure 7: Simulated average excess returns (%) sorted into cash-flow risk deciles. Decile 1 (10) corresponds to the highest (lowest) value of cash-flow risk. Cash-flow risk is measured using the covariance between the growth in the ratio of net payout to market value of assets and consumption growth.

Simulated Asymmetric Dependence and Firm Cash-Flow Risk

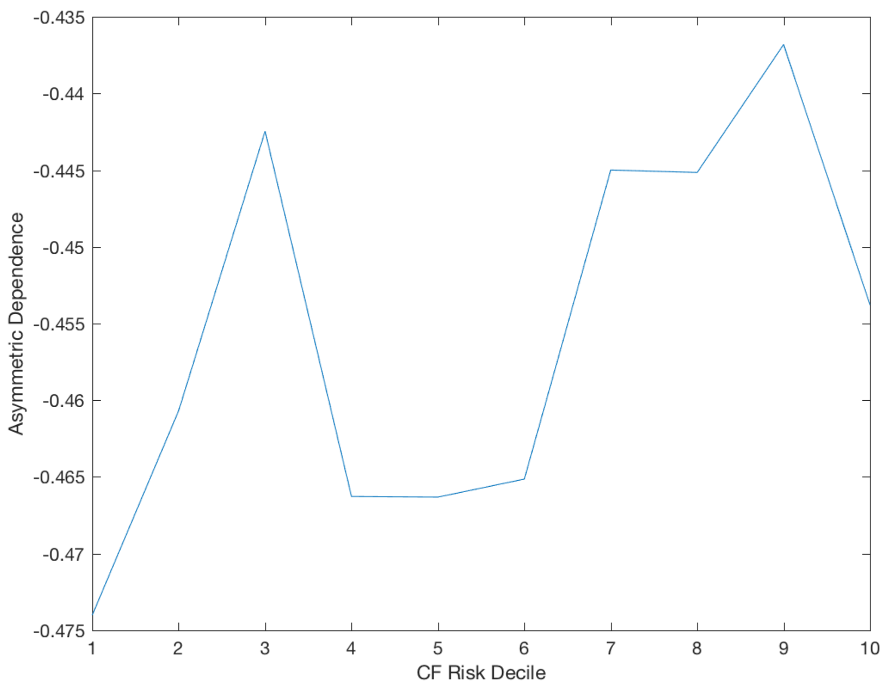


Figure 8: Average values of simulated asymmetric dependence of stock returns, defined in equation (21), sorted into cash-flow risk deciles. Decile one corresponds to the highest level of cash-flow risk.

The Cross Section of Stock Returns vs Cash-Flow Risk

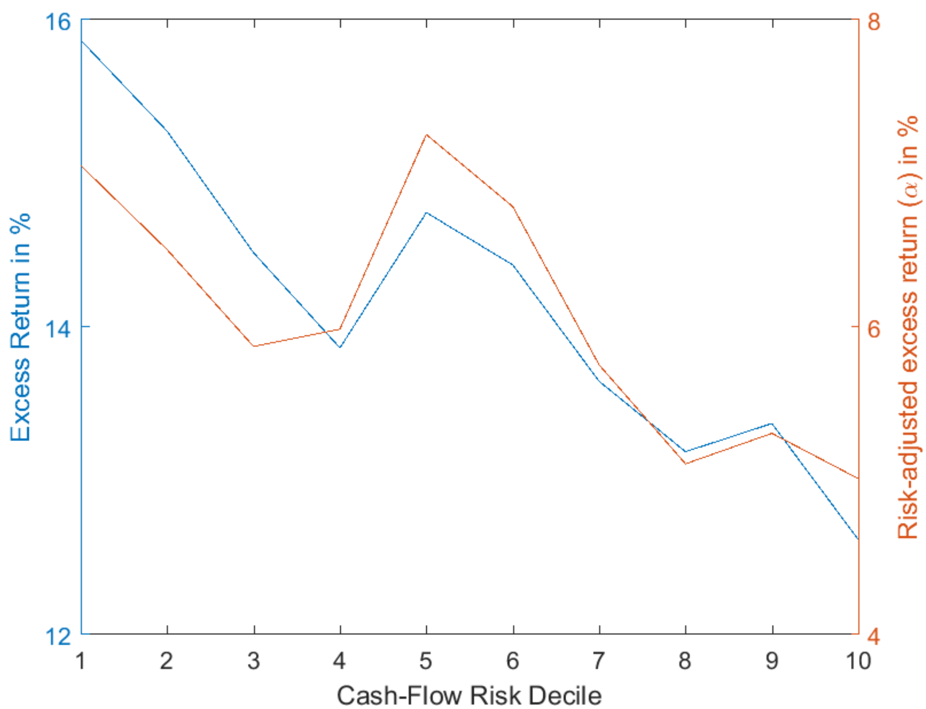


Figure 9: Average excess returns (%) and risk-adjusted excess returns (%) sorted into cash-flow risk deciles. Decile 1 (10) corresponds to the highest (lowest) value of cash-flow risk. Cash-flow risk is measured using the covariance between the growth in the ratio of net payout to market value of assets and consumption growth. All US listed stocks are considered (1960-2016).

Conditional Values and Firm Cash-Flow Risk

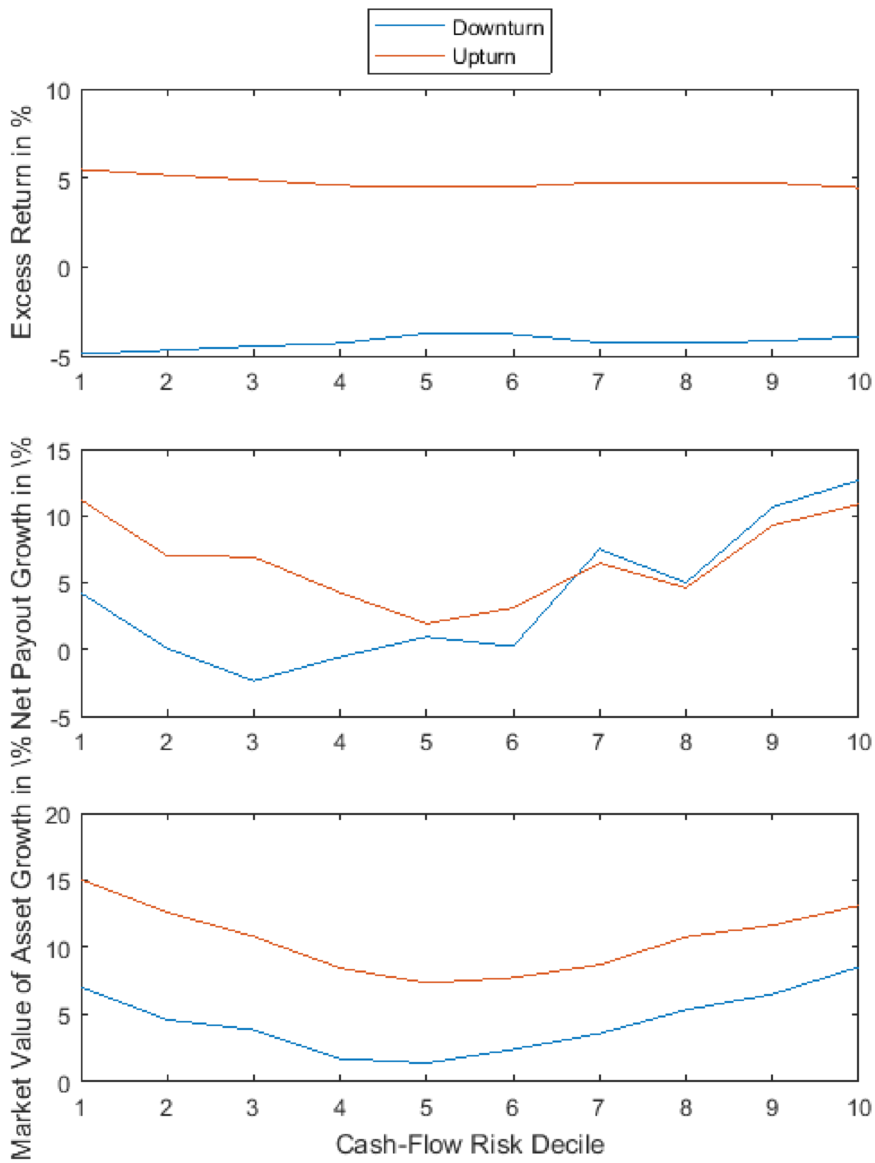


Figure 10: The conditional firm excess return, net payout growth, market value of asset growth sorted into cash-flow risk deciles, where decile 1 corresponds to the decile with highest values of cash flow risk. This figure shows conditional values during market downturns and upturns, where market downturn (upturn) is a situation when the monthly market excess return is lower (greater) than zero. All US listed stocks are considered (1960-2016).

Asymmetric Dependence and Firm Cash-Flow Risk

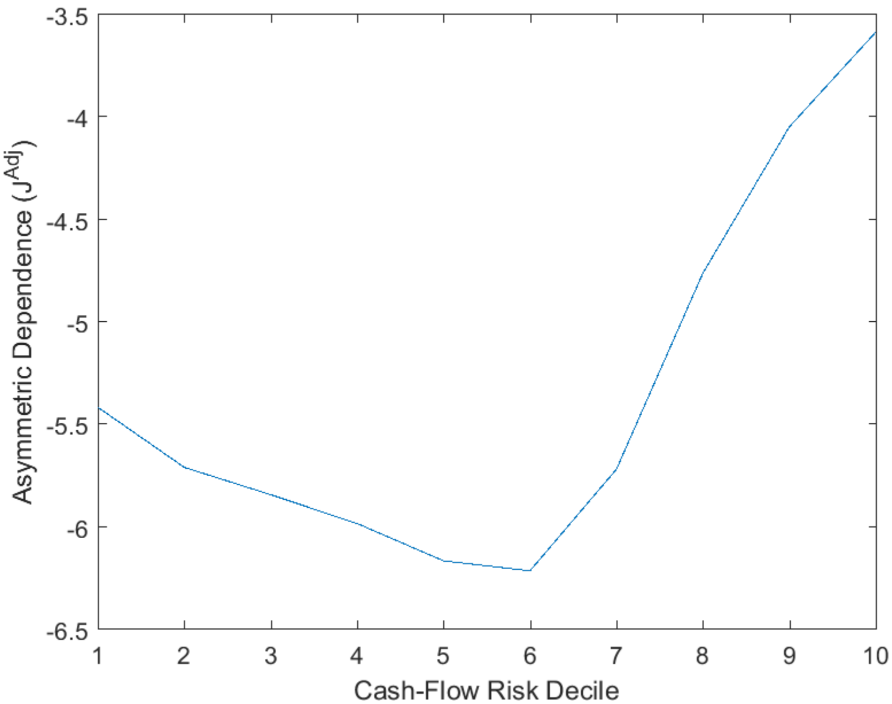


Figure 11: Average values of asymmetric dependence of stock returns, measured using the Alcock and Hatherley (2016) Adjusted-J statistic, sorted into cash-flow risk deciles. Decile one corresponds to the highest level of cash-flow risk. All US listed stocks are considered (1960-2016).

Table 2: Cash-Flow Items. Descriptive Statistics for cash-flow items used to estimate net payout and firm cash-flow risk. The values represent the values of items as a fraction of market value of assets. Asset return is the annual growth in market value of assets. Net payout growth is the annual growth in the ratio of net payout to market value of assets. All US listed stocks are considered (1960-2016).

Cash-Flow Item (% of MVA)	Mean	STD
Net Payout	4.662	136.806
Dividends	0.962	4.703
Net Equity Repurchase	1.764	57.822
Equity Repurchase	0.816	3.922
Equity Issuance	2.578	58.212
Interest	2.107	147.043
Net Debt Repurchase	1.058	104.835
Debt Repurchase	6.934	22.803
Debt Issuance	0.912	2.446
Asset Return	8.175	43.256
Net Payout Growth	5.000	164.091

Table 3: Cash-Flow risk vs the cross section of stock returns. All US listed stocks are considered (1960-2016). The measured values are sorted into cash-flow deciles. Decile one corresponds to the highest level of cash-flow risk. CAPM is used to estimate β and α for each stock individually using all available data. The estimation is in-sample. All US listed stocks are considered (1960-2016).

Decile	1	2	3	4	5	6	7	8	9	10
CF risk	2.224	0.292	0.092	0.030	0.006	-0.007	-0.032	-0.106	-0.401	-4.050
Excess Ret.	0.159	0.153	0.145	0.139	0.147	0.144	0.136	0.132	0.134	0.126
β	1.315	1.274	1.248	1.220	1.134	1.159	1.221	1.194	1.160	1.057
α	0.071	0.065	0.059	0.060	0.073	0.068	0.058	0.051	0.053	0.050

Table 4: Estimated parameters for stocks sorted into CF risk decile. This table shows the mean reversion parameter (ϕ^j), the mean and the volatility of the consumption share of risky asset j ($\bar{s}^j$ and $\sigma(s^j)$). These value are used to simulate from the model for ten portfolio sorts. All US listed stocks are considered (1960-2016). All values are in % points.

Decile	1	2	3	4	5	6	7	8	9	10
CF risk (θ^j_{CF})	10.871	3.075	1.366	0.616	0.192	-0.083	-0.396	-0.991	-2.413	-9.657
ϕ^j	4.150	3.414	3.503	2.620	3.579	4.792	4.686	5.680	4.466	2.852
$\bar{s}^j$	0.132	0.164	0.189	0.259	0.282	0.228	0.335	0.187	0.144	0.163
$\sigma(s^j)$	3.618	3.830	4.354	5.776	9.207	6.490	9.868	5.054	3.449	4.061

Table 5: Conditional Values and Cash-Flow Risk. All US listed stocks are considered (1960-2016). The conditional values of stock excess returns, net payout yield and market asset value growth are measured during market downturns (i.e. when market excess return is negative) and market upturns (i.e. when market excess return is positive). The conditional values are sorted into cash-flow deciles. Decile one corresponds to the highest level of cash-flow risk. The superscript $-$ $(+)$ is related to market downturn (upturn) conditional values. All US listed stocks are considered (1960-2016).

Decile	1	2	3	4	5	6	7	8	9	10
r_i^-	-4.90%	-4.68%	-4.46%	-4.29%	-3.73%	-3.79%	-4.25%	-4.25%	-4.17%	-3.91%
r_i^+	5.48%	5.15%	4.89%	4.57%	4.48%	4.50%	4.73%	4.75%	4.71%	4.45%
NP^-	4.24%	0.07%	-2.35%	-0.57%	0.94%	0.23%	7.50%	5.00%	10.65%	12.68%
NP^+	11.19%	7.01%	6.92%	4.25%	1.94%	3.11%	6.46%	4.62%	9.28%	10.87%
MVA^-	7.04%	4.61%	3.86%	1.73%	1.40%	2.40%	3.59%	5.35%	6.51%	8.55%
MVA^+	15.04%	12.61%	10.80%	8.45%	7.35%	7.74%	8.70%	10.77%	11.65%	13.10%

Table 6: Cash-Flow Risk vs Asymmetric Return Dependence. All US listed stocks are considered (1960-2016). Cash-flow (CF) risk is the covariance between cash-flow and consumption growth. Decile one corresponds to stocks with the highest levels of cash-flow risk. The asymmetric dependence is measure using the J^{Adj} statistic proposed by Alcock and Hatherley (2016). Negative values of J^{Adj} refer to lower-tail asymmetric dependence, which is a situation when returns are relatively more correlated during market downturns than upturns. All US listed stocks are considered (1960-2016).

Decile	1	2	3	4	5	6	7	8	9	10
CF risk	2.224	0.292	0.092	0.030	0.006	-0.007	-0.032	-0.106	-0.401	-4.050
AD (J^{Adj})	-5.415	-5.709	-5.842	-5.983	-6.165	-6.214	-5.718	-4.761	-4.047	-3.584