Essays on Firm Financials and Stock Returns

—Evidence from Monetary and Asset Pricing Perspectives

by

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ABSTRACT

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This dissertation studies the link between firms' external financial constraint and stock returns. Having identified the difference between financial distress and financial constraint (non-distressed), the paper investigates both problems separately. 1) Based on Bernanke, Gertler, Gilchrist (1999)'s theory on the financial accelerator, I show that firms' leverage can capture firms' exposures to distress risks. Sorting firms by their leverages and book to market ratios, the stock price only incorporates distress risk for value firms since the sensitivities of stock returns to unanticipated monetary shocks (measured in absolute values) are lower for highly leveraged growth firms. 2) I also explore the financial constraint puzzle in asset pricing literature by using Campbell and Vuolteenaho (2004)'s two-beta model. By decomposing stock's return into cash flow news and discount rate news, I am able to explain why financially constrained stocks do not yield a positive return premium over unconstrained counterparts and why financially constrained stocks tend to move together.

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Chapter 1

Introduction

The pioneered work by Bernanke, Gertler and Gilchrist (1999) raises the idea of external finance premium. According to this theory, information asymmetries and other financial frictions make the cost of external financing more expensive than the cost of generating funds internally. It is believed that the cost of external finance depends critically on firms current financial health, or the strength of balanced sheet. So fund-raising activities of those firms with relatively poor financial health (ie lower collateral and more debt dependent) is constrained by the overall credit condition of the market. Consequently, their investment, sales and earnings have larger exposure to aggregate economic shocks.

Although it is straightforward for someone to realize the importance of external finance constraint in real activity, it is somewhat complicated to fully understand its importance in determining asset prices. For long, a firm's financial position is believed to be irrelevant since Modiliani-Merton theorem states the equity values of a firm should not be affected by its financial decision, whether it is debt-financed or equity-financed. Although this prediction has been challenged by numerous empirical findings, theoretical interpretation as how financial constraint is connected to equity prices is still needed to support the argument.

Intuitively, a firm with higher external finance costs might mean two things. First, it might mean higher exposure to distress risk. This type of firms usually are more sensitive to aggregate shocks such as monetary shocks. Second, higher external finance costs might also mean better growth opportunity. A young firm with plentiful investments to be financed might be "cash thirsty" and look for external finance as well. It is expected to yield higher cash return in the distant futures, but it is unlikely to default. In finance literature, the former type of firms are considered as "financially distressed" while the later type are "financially constrained". While for both cases, firms with higher finance costs are unambiguously riskier. But the risks they have incorporated are different. To form a panoramic view of the issue, one has to treat both cases differently.

This dissertation is trying to explore the intrinsic link between firms' equity values and firms' financial. It comprises two essays. The first one (as in chapter 2) investigates the importance of external finance costs from a monetary perspective. More specifically, it addresses this problem: how stock returns of the firms with higher external finance costs responds to exogenous monetary shocks comparing with low-cost firms. The empirical results show that financial distress risk is only incorporated in those firms with lower growth opportunity. Hence a firm with higher external finance might also imply higher return on capital in equilibrium, sending attractive signals to outside investors.

In chapter 3, the second paper focuses specifically on those financially constrained stocks. Using a nonconventional indicator to measure financial constraint, one is able to pick out financial constrained but not distressed firms. When a firm is immune from distress risk, a simple statement for its stock is that: they are riskier in yielding cash flow and they should yield higher returns. However, empirical findings on the financial constraint premium–return difference between constrained and unconstrained ones are always insignificant. The decomposition of returns by using Campbell and Vuolteenaho (2004) implies that cash flow is not the only source for financially constrained stock returns. The premium and comovement can be complicated by investors' irrational pricing as well.

The main contribution of this dissertation is to extend the use of theoretical financial accelerator models in evaluating stock returns. Hence one can recognize the mixed property of external financial constraint. The paper also adds on existing literature regarding financial constrained stock returns. The approach used in this paper is effective to separate rational and non-rational components of stock returns.

Chapter 2

External Finance Constraint and Stock Returns–Evidence from Impacts of Monetary Shocks

2.1 Introduction

How can monetary policy affect the financial markets? Conventional macroeconomic wisdom believes the channel for monetary policy is the real interest rate: in the standard IS-LM framework, monetary policy changes the market equilibrium interest rate, which mainly affects equities' value through the wealth effect. (ie. change of real interest rate triggers the shift of intertemporal substitution between current and future consumptions)

On the other hand, if investors see real interest rate as the only channel for monetary policy then we should expect all the stock respond to monetary shock uniformly (or at least, in a similar way) after the FOMC meetings: since the real interest rate only reflects the rate investors use to discount the future cash flow, given that future expectations on firms' cash flow remain constant, then the stock prices for every public traded firm should adjust by the same amount. However, a lot of empirical studies contradicts this prediction. For example, Thorbecke (1997) uses identified VAR system to show different reactions to monetary shock at portfolio level. He finds that the smaller firms (in the lowest deciles) tend to be more sensitive to the monetary shock. Also Ehrmann and Fratzscher (2004) find the similar pattern by using event study approach. All these pioneering papers cast the doubts on "conventional wisdom" regarding the interest rate channel and lend support to the "credit view" or "credit channel" of monetary policy, which argues that firms do exhibit different cost of external financing due to the existence of financial friction such as information asymmetry.

This paper explores the credit view on stocks' reaction to monetary shocks. Unlike the existing literature that only focus on empirical estimates of the responsive coefficients, my approach is motivated by theoretical modeling of firms' credit risk by Bernanke, Gertler and Gilchrist (1999). I argue that monetary shocks are related to firms' distress risks, and firms' exposures to credit risk depend on their leverages. I also find that stocks' sensitivities to monetary shocks are jointly determined by firms' expected rate of return on capital as well as leverages.

The term "credit view" or "credit channel" of monetary transmission is first introduced by Bernanke and Blinder (1992) when they are trying to interpret the passive response of bank loans to the Federal funds rate. The credit channels of monetary policy affect the real economy in two ways. One is the supply of credit, which is about the behavior of lending institutions; the other one is on the demand for credit, or so-called balanced sheet channel, which is built on the assumption that firms' demand for capital is constrained by its strength of balance sheet. The cost of external finance is inversely related to the firm's net worth. Consider a firm with a relatively less collateral and more bank loan dependent, then it would suffer more from the increasing interest costs and reduction in positive cash flow when market interest rate rises. This countercyclical behavior of external finance constraint further affects the firm's earnings and investment. The empirical support for "the balanced sheet channel" is first found by Gertler and Gilchrist (1994), when they find smaller firms contract more in the period of credit tightening. The sales and inventory of smaller firms are also more sensitive to the monetary shocks and tend to be instable around the Romer dates. Later on, Bernanke, Gertler and Gilchrist (1999) (henceforth BGG) derive a general equilibrium model under the assumption of costly verification state and show the critical link between monetary policy and the financing decisions of firms is the credit: firms that are highly leveraged face higher probability of distress and higher costs of capital. In order to pay back expensive costs of external financing, naturally those firms require a higher rate of return on the projects that they finance. Their paper provides an endogenous framework on how credit market frictions influence capital structures of firms.

Nevertheless, for investors on the financial markets, a natural question to ask is: how this financial friction or the credit channel affects prices of the stocks? To the extend that a firm is leveraged, its equity value vary accordingly. For instance, contractionary monetary shock raises distress probability, and firms with higher distress risks usually yield lower returns on stocks (see Campbell, Hirshleifer and Szilagyi, 2008). On the other hand, higher market interest rates allow only high-yield projects to be financed, given that firms' accounting return (ie. ROE) is positively related to stock returns, firms with higher leverages should have higher returns on stocks(see Zhang et al, 2009). The existence of both effects can be responsible for empirical observation by Ehrmann and Fratzscher (2004), Peersman and Smets (2002) and Dedola and Lippi (2000) such that estimated responsive coefficients are not monotonic across leverage-sorted groups. Sorting sample firms on book-to-market ratios and leverages, I find that highly leveraged growth firms are less sensitive to monetary shocks while highly leveraged value firms are more sensitive to monetary shocks.

The paper is organized in the following: Section 2 discusses some implications about the BGG model and shows the testable hypotheses in the model; section 3 describes the data and investigates the relationship between bankruptcy rates and external finance premium; section 4 presents the major empirical results on stock reaction to monetary shocks using characteristic-sorted portfolios; section 5 does a robustness check with firm-level data; and section 6 concludes.

2.2 Theoretical Framework

The model is mainly based on Bernanke, Gertler, Gilchrist (1999), but there are several major differences introduced. First, BGG model is a general equilibrium model, so all its results are evaluated at the aggregate level. However, my goal is to compare the effects of monetary policy on firms, especially cross-sectionally, so my result can be viewed as a partial equilibrium. So some economic shocks such as return on capital and monetary rules are simplified as exogenous while in a general equilibrium model, their dynamic process must be considered in a complex system together with other state variables. However, I argue this would not affect our empirical result too much since I study the "shocks" rather than entire components of those state variables which somehow produces "clean" proxies for empirical studies. (we will go more detail in section 3)

Second, in order to test the cross-sectional responses of firms to monetary policy, I disaggregate my sample to two groups: firms with a high growth opportunity recognized by the public and ones with a low growth opportunity. By doing so, the meaning of leverage has been enriched: it is not only a proxy for higher probability of financial distress, but also somewhat reflects the quality of the firm's growth opportunity. so that it can pay off its debt in the future. Also by grouping the firms, it justifies the necessity of portfolio studies for empirical analysis, which trades off the difficulty of studying firm-level stock return since it contains too much idiosyncratic volatility.

I start firms' capital investment decision in the same context as BGG's two-period model. At time t, firm j decides its expenditures on capital to be used in time $t+1$, K^j_{t+1}. At the same time, firm j has its net worth N^j_{t+1}, which is smaller than its capital demand. So it has to finance the difference through debt, such that $B^j_{t+1} = K^j_{t+1} - N^j_{t+1}$. And the gross interest rate on the debt is given by Z^j_{t+1}.

At time $t+1$, the ex post return on capital for firm j is $\omega^j R_{t+1}$, where ω^j is firm j's idiosyncratic shock with $E(\omega^j) = 1$ across firms and its density function of $f(\omega)$. So when making financing decision, the firm has to decide its optimal capital demand based on conditional expectation on R_{t+1}. Therefore, firm j's objective is to maximize its expected firm value such that

$$E(R_{t+1})K^j_{t+1} - B^j_{t+1}Z^j_{t+1} \tag{2.1}$$

Clearly, the firm is possible to end up with default at time $t+1$. So for the lender, it has to decide a threshold value $\bar{\omega}^j$, such that for any values of ω^j smaller than $\bar{\omega}^j$, the firm defaults. Therefore, it can be defined as

$$\bar{\omega}^j R_{t+1} K^j_{t+1} = Z^j_{t+1} B^j_{t+1} \tag{2.2}$$

Also following CSV assumption, there is an un-diversifiable default cost when the firm fails, so the expected payoff to the lender is given by the following

$$[1 - F(\bar{\omega}^j)]Z^j_{t+1}B^j_{t+1} + (1-\mu)\int_0^{\bar{\omega}} \omega R_{t+1} K_{t+1} f(\omega) d\omega \tag{2.3}$$

where μ captures the auditing cost when the firm is liquidated. So if the lender is risk neutral, then equation 2.3 has to equal to the corresponding payoff on the riskless asset, $R_f B^j_{t+1}$. Hence, we have

$$[1 - F(\bar{\omega}^j)]Z^j_{t+1}B^j_{t+1} + (1-\mu)\int_0^{\bar{\omega}} \omega R_{t+1} K_{t+1} f(\omega) d\omega = R_f B^j_{t+1} \tag{2.4}$$

So the optimal contract problem now becomes quite obvious: each firm chooses optimal capital expenditure K^{*}_{t+1} as well as $\bar{\omega^{*}}$ (which is associated with bankruptcy risk) to maximize equation 2.1 and subject to equation 2.2 and 2.4.

BGG derives the first order conditions as the following

$$K^{j*}_{t+1} = \Psi(\bar{\omega})N^{j}_{t+1}, \quad \Psi'(\bar{\cdot}) > 0$$

$$s_t = \rho(\bar{\omega}), \quad \rho'(\bar{\cdot}) > 0$$

$$K^{j*}_{t+1} = \phi(s_t)N^{j}_{t+1}, \quad \phi(1) = 1, \ \phi'(\cdot) > 0$$

where $s_t = \dfrac{E_t R_{t+1}}{R_f}$ denotes the external finance premium. This set of equations shows monotonic relationships among default probability, leverage and external premium. It has two interesting interpretations. First, due to the existence of default cost, the expected return on the project to be financed has to exceed the riskless rate unless the firm has enough net worth to finance the project itself. Second, a rise in expected discounted return on capital stimulates demands for capital proportionally, and also increases the default probability.

With this critical link derived, BGG is able to simulate the dynamic of corporate investment at aggregate level. Yet our interest is to explain the cross-sectional differences of firms. So instead of aggregating, I assume there are two types of firms: one with high growth opportunity $E_t R_{H,t+1}$ and one with low growth opportunity $E_t R_{L,t+1}$, with $E_t R_{H,t+1} > E_t R_{L,t+1}$. The reason that I categorize firms in terms of their growth opportunity is based on massive empirical observations on the importance of growth opportunity as an determinant of firm's performance in both asset pricing and corporate finance literature. Fama and French's (1992, 1993) celebrated papers show that growth opportunities of firms (measured by book to market ratio) can explain the cross-sectional differences in the return of sorted portfolios. Moreover, Laknoish, Shleifer and Vishny (1994) find further support on the effect of growth opportunities after they design several different ways of defining "growth" and "value" firms. Furthermore, there has also been found some evidence on the link between growth opportunity and firms' external financing ability. Lang et al (1996) shows that only those firms with poor investment opportunity tend to have a negative relationship between leverage and performance, but not for firms with good investment opportunity. This suggests that a firm with a good investment prospective can always find funding no matter how bad its balance sheet looks like. All these findings inspires me to categorize firms according to their growth opportunities.

Having documented the motivation to revise the model, I further assume both entrepreneurs and banks have a common perception about what class a firm should belong to and they both know the mean return on capital of the group. The rest of model remains the same as BGG. Firms make financing decision at time t and for the firms in the "growth" (value) group, comparing with its counterparts, it expects to yield at least $E_t R_{H,t+1}$ ($E_t R_{L,t+1}$) in order to have its project financed. Hence, when this condition binds, it yields similar result as

$$K_{t+1}^{j*} = \Psi(\bar{\omega}_i) N_{t+1}^j$$

$$s_{i,t} = \rho(\bar{\omega}_i)$$

$$K_{t+1}^{j*} = \phi(s_{i,t}) N_{t+1}^j$$

Moreover, with categorical information available, investor now can discriminate the equity value across firms. Combining the results from equation 2.1 to 2.3, a firm j in the category of i who survives at $t+1$ should have its ex post value as

$$V_{t+1}^j = \omega^j R_{i,t+1} K_{t+1}^j - \frac{(K_{t+1}^j - N_{t+1}) R_f - (1-\mu) \int_0^{\bar{\omega}} \omega f(\omega) R_{i,t+1} K_{t+1}^j d\omega}{1 - F(\bar{\omega})}, \; i = H, \; L \tag{2.5}$$

Notice that in each group, there is a constant fraction $F(\bar{\omega})$ of firms who fail. So the ex post value of each group can be aggregated in such a fashion

$$V_{i,t+1} = R_{i,t+1} K_{i,t+1} - [R_f (K_{i,t+1} - N_{i,t+1}) + g(\bar{\omega}, \mu) K_{i,t+1}] \tag{2.6}$$

where X_i denotes the portfolio-level state variable. For instance, $K_i = \int_{\bar{\omega}}^{\infty} f(\omega) K^j d\omega$. And $g(\bar{\omega}, \mu) = \mu \int_0^{\bar{\omega}} \omega f(\omega) d\omega$, which reflects the default costs and the premium for external finance. (Notice if the firm use its net worth to finance the project, it only needs to pay the opportunity cost equaling to the market risk-free rate.)

Also the ex ante value of each group can be obtained by taking conditional expectation on equation 6

$$E_t V_{i,t+1} = E_t R_{i,t+1} K_{i,t+1} - [R_f (K_{i,t+1} - N_{i,t+1}) + g(\bar{\omega}, \mu) K_{i,t+1}] \tag{2.7}$$

Notice that the interest that the firm has to pay is determined at time t rather than $t+1$, so substituting 7 to 6, one can have

$$V_{i,t+1} = E_t V_{t+1} + (R_{i,t+1} - E_t R_{i,t+1}) K_{i,t+1} \tag{2.8}$$

Therefore, we can derive an expression for percentage change of equity value with respect to an unexpected shift in the return to capital

$$\frac{\partial V_{t+1}/E_tV_{t+1}}{\partial(R_{i,t+1}-E_tR_{i,t+1})/E_tR_{i,t+1}} = \frac{E_tR_{i,t+1}K_{i,t+1}}{E_tV_{i,t+1}} \ \textit{where}\ i = H,\ L \tag{2.9}$$

Equation 2.9 is similar to equation 4.10 in BGG. Interestingly, the change of equity value is determined by the sign of unexpected shift in the return to capital. Supposing there is an unexpected contractionary monetary shock at $t+1$, it forces down the realized return on capital (which might be due to the decline in aggregate demand), to the level that firms are leveraged, the ratio changes across different leverage class; to the growth opportunity that firms are expected to have, the ratio can also vary across growth class. Later on, since the net worth of company is an accumulation of equity value and the wage paid to the managers such that

$$N_{t+2} = \gamma V_{t+1} + W_{t+1}$$

where γ is a constant proportion of equity value going to firm's net worth and W is the wage. The decline in equity value then affects net worth of the firm next period, and the net worth determines how much more external funds can be raised in time $t+2$, it further exacerbates firm's financial constraint and so on.

Conventional monetary theory does not impose "credit" view on the capital demand curve, so it assumes frictionless capital market where $g(\bar{\omega}) = 0$. Further, since there is no such binding mechanism to tie capital demands with the financial health of the firm, the firm will purchase infinite amount of capital as long as $R > R_f$. So equation 2.6 collapses to $V_{i,t+1} = R_{i,t+1}N_{i,t+1}$. When there is an unexpected shift in nominal interest rate, the riskless rate is served as the only channel for monetary transmission. Moreover, it does not impose further impact of the shift. Since as long as the firm survives, it can freely access to new capital until its return reaches the risk-free rate. So the effect of monetary policy has been amplified or "accelerated" if one believes the existence of credit channel. Ceteris paribus, the effect of monetary policy is more profound and more persistent with the presence of financial accelerator. Secondly, after grouping into respective two classes, it is quite obvious that the response of stock prices is determined not only by its capital structure, so to speak, the financial health of its balance sheet, but also depends on its growth opportunity. This can partially explain recent empirical findings about "nonlinear" puzzles of leverage effects on stock responses to monetary shocks by Ehrmann and Fratzscher (2004), Peersman and Smets (2002) and Dedola and Lippi (2000). When sorting stocks simply based on their leverages, the effect of growth opportunity is damped. In order to reconcile both effects, I take both portfolio-level and firm-level regression to investigate the effects of monetary policy.

Based on the model, I formulate 2 hypotheses for empirical testing

Hypothesis 1 *Default frequency should be positively related to firm's leverage*

Hypothesis 2 *The return of the stock should respond negatively to monetary shocks, and its sensitivity to monetary shocks should depend on firm's leverage as well as expected growth opportunity.*

Hypothesis 1 is simply from the first order condition itself, and this allows me to test cross-sectional properties of leverage and default probability. To reinforce my argument, I also compare firms' real activities across different leverage group. Hypothesis 2 is the main purposes of this paper. The intuition is that if the credit channel can be perceived by the market through some balanced sheet factors then it must follow the disparity in the stock returns across different firms with heterogenous characteristics. If market believes growth firms are highly leveraged because of higher earning potential and their desire to discern themselves from value firms, or simply, market is more tolerant to high leverage for growth firms, then it should not follow a positive relation between firm's sensitivity to monetary shock and its leverage. On the contrary, if a highly leveraged firm is believed to have a financial distress in the future, then leverage implies credit risk so it should be more sensitive to those exogenous shocks. This paper provides an alternative explanation to asset pricing from macroeconomic perspective.

2.3 Empirical Results for Default Probabilities

In BGG model, one of the direct predictions is that leverage should be positively related to default probabilities. (*Hypothesis 1*) I extract the firm-level financial data from Compustat Fundamental Annual database and the sample period extends from fiscal year 1962 to 2006. I excludes all the firms in financial industry since their accounting rule is quite different from rest of our observations. Leverage is constructed as the ratio of the book value of long-term debt to the total assets.

To investigate the cross sectional differences in default probabilities, one has to form some measure of default probabilities. The most straightforward indicator is the bankruptcy frequency. It has been used by many other researchers in corporate finance for cross-sectional comparison such as Oopler and Titman (1996). However, it has drawbacks. When measured on a yearly basis, the number of de-listed firms are usually close to 0, so it makes harder to observe the variation of default probabilities because of limited sample size in Compustat. Moreover, the data itself contains survival bias. So I also use "implied" default probabilities–Z index proposed by Altman (1968). This popular indicator in the study of bankruptcy is constructed by a parameterized equations with several key financial ratios. The great advantage is that the Z index is available for each firm and year so long as those ratios for calculation are available. Consequently, higher Z index implies lower default probability. I use Altman's (1968) original parameters to get the Z index for each firm-year although a robustness check using recent data shows quite a consistent result.

To start off, I sort all the firms into 3 leverage classes based on their last year's leverage ratio, firms are grouped in high (80th percentile or higher), medium (20th to 80th percentile) and low (20th percentile or lower) leverage classes. The bankruptcy frequency is defined as average proportion of firms who are in the database in fiscal year t-1 but exists due to bankruptcy or liquidation in fiscal year t. For Z index, I follow Altman's (1968) procedure and construct Z index based on relevant financial ratios in year t. Then the medium Z value of each leverage class is reported and averaged over time. To see whether the default probabilities vary across growth and value groups, I also sort the firms whose book-to-market ratio are greater than 1 into "value" class, while those firms whose book-to-market ratios are smaller than 1 into "growth" class (Detailed reasons are covered in section 2.2). Intersecting with my leverage classes, I compare high leverage and growth, low leverage and growth, high leverage and value, as well as low leverage and value.

The cross-sectional comparison seems support *hypothesis 1* that default probabilities increase as firms' leverages increase. Sorting one way by leverage, both measures are quite consistent to the theory. Highly leveraged firms have high failure rate of 5.35% whereas low leveraged firms have lower failure rate of 5.05%. The two-way sorting suggests similar results. Due to insufficiency of the data, the bankruptcy rates are equal to 0 for most of years. That is probably the reason why all three sorting schemes show the economically different results in failure frequencies but do not show statistical significance. An even better result is obtained when we use Z index. The Z index is almost two times greater for those low leveraged firms. This implies that leverage is an idea proxy for financial distress risks no matter how well the market perceives the firms to be. Whether growth or value, a firm with higher leverage have higher exposure to default risks.

Additionally, I test whether a firm's capitalization or size can reflect its exposure to distress risk. When I sort the firms by size, Z index is however larger for those small firms, which is quite counterintuitive. One possible explanation is that those firms in COMPUSTAT are mostly public firms, who all represent a class of large firms in the market. So the differences in size of our sample may not be large enough to capture the differences in firms' access to capital markets hence size is not a good proxy for cost of external finance .

Table 1: Cross-sectional Comparison of Bankruptcy Probabilities by Leverage and Book-to-Market

	Mean Bankruptcy Frequency	Medium Z Index
High leverage	5.35	76.15
Low leverage	5.05	160.14
t stats for High-Low	0.53	-17.94
High leverage and Growth	7.90	80.73
Low leverage and Growth	6.75	147.14
t stats for High-Low (growth)	1.14	-14.34
High leverage and Value	4.79	73.57
Low leverage and Value	4.14	163.61
t stats for High-Low (value)	1.16	-18.68

This table reports mean bankruptcy frequency (in percent) and Altman's Z index. The growth firms are those firms whose book-to-market ratios are smaller than 1.

Next I examine the firms' performance cross-sectionally. Table 2 shows the comparative results between leverage groups. The first measure of performance is the firm's capital expenditure as a ratio to total assets. I choose this one as it directly measures the firm's demand for capital. If leverage is a proxy for external premium, then we would expect higher ratio in highly leveraged firms. Our data confirms this proposition. Highly leveraged firms by average have a capital/assets ratio equal to 6.57% while firms in my low leverage sample only have 4.56%. And the difference is statistical significant.

Table 2: Cross-sectional Comparison of Performance by Leverage

	Capital Expenditures	Sales Growth	Operating Income
High leverage	6.57	9.92	11.70
Low leverage	4.56	11.24	11.57
t stats for High-Low	5.67	-1.51	0.13

This table compares accounting ratios across leverage groups. Capital expenditure is the capital expenditure as a percentage of total assets, sales growth is the percentage change from year t-1, and operating income is the operating income as a percentage of total assets.

The next indicator I use is the sales growth. Oopler and Titman (1996) finds sales growth of highly leveraged firms are more likely to be affected by indirect costs of financial distress. So if leverage proxies the probability of distress, then sales growth should be lower for high leverage group. However, one caveat should be noticed sales growth can be manager driven too. As we will discuss later, managers can manipulate sales growth to send out a good signal to investors. That is why my comparison in sales does not produce significant results. Similar pattern can be found in operating income ratio to total assets: no significant difference can be found between high and low leverage groups. These inconclusive results, on the other hand, indicate that firms' performance might also be driven by some other factors. The leverage alone can have mixed implication toward how well the firm is functioning, which in turn, shed the light on the necessity of examining growth opportunity in our studies.

2.4 Portfolio-level Return Responses to Monetary Shock

This section examines how stock prices respond to monetary shock. Existing literature such as Bernanke and Kuttner (2005), Rigobon and Sack (2004) has already found aggregate stock return is negatively related to exogenous shocks. On the other hand, relatively little evidence has been found on individual stock return to monetary shock. Exceptions are Ehrmann and Fratzscher (2004) who use event study approach to analyze cross-sectional responses of SP 500 stocks to unexpected monetary shock around FOMC meeting dates, and Perez and Timmerman (2000) who find small firms are more strongly affected by monetary shock in the recession. The disparities in responses to monetary policy are at least due to two reasons. The first is that the monetary policy can have sectorial or industry effect. The demands for the goods and services in different industries might exhibit different sensitivities to interest rate and inflation. For instance, one might expect relative stronger demand shifts of cyclical durable goods such as cars versus non-cyclical durable goods such as food when credit condition changes. Also due to the fact that production functions in different industries might have different elasticities of substitution on capital, the interest cost of the firms can vary tremendously. All these can lead to different valuation of firms' stock prices. The second effect is the liquidity effect, which pertains to firms' ability of raising funds in the future.

When comes to empirical test, researchers face two challenges. The first one is to form an exogenous monetary surprise. Asset price is a reflection of all information available including anticipated policy changes, when evaluating policy changes without isolating anticipated and unanticipated components, researchers can end up with endogeneity and simultaneity issues. A large school of monetary economists advocates obtaining monetary surprise terms from a structural VAR system in order to study the link between monetary policy and financial market such as Patelis (1997) and Thorbecke (1997). However, as pointed out by Rigobon and Sack (2004), pure exogenous monetary shock might still be unavailable with VAR system since stock return picks up new information almost instantly. And the problem can be serious with relatively lower frequency data. To see this, consider on the day D of month T, there is a policy surprise due to FOMC meeting on that day. Instantly after the meeting, market should respond to the new information. Later on in the month, more shocks arrive and change the market's expectation about stock prices as well as anticipated monetary policy stance. When one observes the data in monthly or even quarterly frequency, those extracted structural shocks contain both unanticipated movement on day D and revised expectation from day D and on.

The market-based measure for monetary expectation is first introduced by Kuttner (2001) where he uses Federal funds future prices as a proxy for market expectation about monetary policy. The future starts trading on CBOT (Chicago Board of Trade) in 1989, and its delivery months vary from spot month (end of the current month) up to 2 years. It is betting on the spread between monthly moving average of Federal funds effective rate and the settlement price of the contract. So, by all means the future price should reflect market participants' anticipation about fed funds rate target in the future. For instance, the closing price of one-month ahead contract on the last day of month t-1 can be expressed as

$$f^1_{t-1,D} = \frac{1}{m} E_{t-1} \sum_{d=1}^{m} i_{t,d} + \mu \tag{2.10}$$

where m is the number of days in month t, $i_{t,d}$ is the daily Federal Funds target rate and μ is the premium accruing to investors long in the spot-month futures contract. So the surprise term at monthly frequency can be simply derived as

$$\bar{\Delta} i^u_t = \frac{1}{m} \sum_{d=1}^{m} i_{t,d} - f^1_{t-1,D} - \mu \tag{2.11}$$

Given that μ is usually not too large, it can be regarded as an unexpected component of monetary policy. The greatest advantage of this market-based measure over VAR form is that it does not require additional assumption on the system. In addition to Federal funds future, researchers also develop some other instruments to form market-based measures of monetary policy. For instance, Cochrane and Piazzesi (2002) use the one-month eurodollar deposit rate, Ellingsen and Soderstrom (2004) use the three-month Treasury bill rate, and Rigobon and Sack (2002) use the three-month eurodollar futures rate. In this paper, I use the one month Federal funds future price as a proxy for market expectation about monetary policy.

The test of differences in responses of stock prices to monetary shock can also be complicated by the fact that capital demands and the spread between expected return of capital and risk free rate is intrinsically interwound and endogenously determined. The exogenous shocks such as productivity or monetary policy, can change expected return on capital and this further shifts the demand schedule of capital. As my previous derivation shows, the sensitivity of ex post stock price to monetary shock (or any shock that induces change of unexpected return on capital) depends on leverage of the firm and expected return on capital henceforth the growth opportunity of the firm. While it is easy to observe a firm's leverage, it is usually difficult to form the expected return on return quantitatively.

On the other hand, inspired by Tobin (1969), Tobin's q (or its inverse book to market ratio of equity) has been implemented as a proxy for firm's growth opportunity in many corporate finance literature. Tobin's q is defined as a ratio between the market value and replacement value of the same physical asset, which is book value per se. If a firm has a valuable investment opportunity known to outsider, it has to be reflected on the firm's stock prices. This will drive up the market value of the firm, so a growth firm usually have a higher Tobin's q (or lower book to market ratio).

Therefore, I double sort all the firms in the same fashion as I do in section 2.1. Both growth and leverage classes are re-balanced and formed by the end of June every year using COMPUSTAT accounting information. To make sure the public availability of accounting information at time t, I allow at least 6 month gap between the portfolio formation period and the return observation period. For instance, if a firm's fiscal year end is June in year t, its corresponding return observation starts from June of year $t+1$. Similarly to the data processing procedure before, I exclude those firms in financial industry. And in order to be compatible with the availability of fed funds future data and to avoid highly volatile period of financial crisis in 2008, my sample period is set from January of 1990 to July of 2008.The Federal funds future is from Thomson DataStream.

The next question is the choice of state variables. As pointed out by the model earlier, the value of the equity can response to any shock that moves the unexpected return on capital. When comes to empiric, the return of stock can be influenced by a huge set of deterministic and nondeterministic factors. Obviously my main goal is not to formulate a new model to include all of those explanatory variables, but to estimate the unbiased effect of monetary policy for our interests of study. For this purpose, the selected state variables should be 1) at least predictive to stock return 2)relevant to monetary shock themselves so that one does not need to bother the infinite sets of choice variables for returns. Fortunately, both monetary and finance literature already provide me a good roadmap for the choice of state variables. It is widely believed among monetary economists, monetary policy should affect at least two things: growth of output and inflation. So in a standard VAR system such as in Bernanke and Blinder (1992), Christiano et al (1996) and Bernanke and Mihov (1998), some proxies for output and inflation are included. Since my data is monthly, I use industrial production growth to proxy for output and change of CPI including sensitive products to proxy inflation. However, because my monetary shock is extracted from purely unexpected components of fed funds futures, I do not include the bank reserves "block" (such as nonborrowed reserves or total reserves) as in most monetary literature. Instead, similar to Bernanke and Kuttner (2005), the monetary surprise term is entered as an exogenous shock in my model.

Because of empirical success of Fama-French three factors model (1992, 1993), I also include financial variables such as SMB (return spread between small-sized and large-sized portfolio) and HML(return spread between high book-to-market and low book-to-market portfolio). As noted by Fama and French (1996), these two risk factors might reflect the business cycles of an economy. Market excess return is also included in my VAR system as for the concern of "beta". Therefore, my VAR system is as following

$$Z_t = A \cdot Z_{t-1} + B \cdot MSUR_t + u_t$$

where

$$Z_t = \begin{pmatrix} DIP_t \\ INF_t \\ SMB_t \\ HML_t \\ MKT_t \\ RET_t \end{pmatrix} \tag{2.12}$$

where DIP is the growth of industrial production, INF is the monthly inflation rate, SMB is the mimic risk factor for size, HML is the mimic risk factor for book-to-market, MKT is the excess return of equal-weighted CRSP return, RET is the equal-weighted return of each portfolio (by leverage and by book-to-market) and MSUR is the monthly monetary surprise computed from equation 2.11 by assuming the risk premium of Federal funds future is zero ($\mu = 0$). The macroeconomic data is from Federal Reserves website, risk factors are from Professor French's data library, and return data is constructed by using Compustat and CRSP merged data set from WRDS. For simplicity, I use VARX(1, 0) since all VAR system with different orders of lags can be stacked into one lag. The idea is to formulate orthogonal shocks for the state variables although one can always argue that the system is not complete. While we are unable to justify the effects of other state variables, the effect of monetary surprise is quite robust due to the fact that pricing error of Federal funds future is uncorrelated with lagged information. (Kruger and Kuttner, 1996)

Table 3 confirms the orthogonality of the market-based monetary surprise. All state variables' correlations with $MSUR$ are close to zero with one exception of the correlation between DIP and $MSUR$ when full sample period is studied. However, when observing the sub-sample period from 01/1994 to 06/2008, the coefficient is insignificant then. One possible explanation could be that the Federal funds rate target is not explicitly stated in FOMC before January 1994, so investors who trade federal funds futures are less informative than after 1994. Knowing this breakpoint is trivial as it has very little effect on my regression result. Another implication from the correlation matrix is that financial variables such as market excess return, SMB and HML are correlated with each other. I use decomposed impulse response analysis to study their impact on portfolio returns.

I first use 5-variable VAR and monetary surprise to see the market overall reaction to monetary shocks. The estimated coefficients on $MSUR$ is -10.056 which is quantitatively similar to Bernanke and Kuttner (2005)'s results. One percentage point shift in monthly monetary shock leads to aggregate market monthly return change by 10 percentage point in opposite direction. Lagged inflation rate also predicts market return, which is consistent with earlier finding by Chen, Roll and Ross (1989).

Next I move to portfolio-level analysis. I estimate 6 portfolios (growth and high, growth and medium, growth and low, value and high, value and medium and value and low) using the same specification individually. By doing so, I allow different factor loadings on each factors as well as different responsive coefficient on monetary surprise. The return is equal-weighted return of sorted portfolio. From table, we can see that, consistent with theory, the growth group overall tends to be more sensitive to monetary shock than the value group (-11.624 vs -7.695) since it has higher expected return on capital. And even more interesting finding lies in the comparison of estimated coefficients across leverage class within each growth class. When ranking leverage from high to low, we can see a decreasing trend of estimated sensitivities for the value group; while a sort of nondecreasing or even increasing trend has been observed among the growth group. Unfortunately, given the limited sample period–221 observations, the asymptotic standard deviation computed from VAR does not seem to provide a reliable statistical evidence for the observed patterns. The last two columns are the estimates for size sorted portfolios. Yet after I control the effects of growth opportunity or maybe due to the selection bias of Compustat (public traded firms are comparably large firms anyway), size

Table 3: Correlation Matrix of VAR State Variables

	01/1994-06/2008					
	MSUR	MKT(-1)	SMB(-1)	HML(-1)	DIP(-1)	INF(-1)
MSUR	1					
	——					
MKT(-1)	-0.036	1				
	(-0.468)	——				
SMB(-1)	-0.028	0.207	1			
	(-0.362)	(2.773)	——			
HML(-1)	0.004	-0.513	-0.480	1		
	(0.054)	(-7.829)	(-7.170)	——		
DIP(-1)	0.045	-0.084	-0.039	-0.009	1	
	(0.595)	(-1.105)	(-0.507)	(-0.117)	——	
INF(-1)	0.042	-0.090	0.038	0.011	-0.116	1
	(0.546)	(-1.188)	(0.502)	(0.145)	(-1.534)	——

	Full Sample					
	MSUR	MKT(-1)	SMB(-1)	HML(-1)	DIP(-1)	INF(-1)
MSUR	1					
	——					
MKT(-1)	-0.080	1				
	(-1.188)	——				
SMB(-1)	-0.041	0.214	1			
	(-0.611)	(3.232)	——			
HML(-1)	0.063	-0.490	-0.435	1		
	(0.930)	(-8.288)	(-7.133)	——		
DIP(-1)	0.208	-0.113	-0.051	0.040	1	
	(3.132)	(-1.679)	(-0.750)	(0.597)	——	
INF(-1)	0.003	-0.148	-0.015	-0.009	-0.080	1
	(0.046)	(-2.202)	(-0.221)	(-0.134)	(-1.182)	——

Table 4: VAR Estimates of Market Excess Return

	DIP	INF	SMB	HML	MKT
DIP(-1)	0.086	-0.005	-0.328	-0.236	0.764
	[1.235]	[-0.170]	[-0.716]	[-0.576]	[1.488]
INF(-1)	-0.138	0.291	-1.451	0.664	-2.686
	[-0.800]	[4.253]	[-1.280]	[0.657]	[-2.118]
SMB(-1)	0.000	0.004	-0.061	0.166	0.037
	[-0.025]	[0.899]	[-0.819]	[2.511]	[0.451]
HML(-1)	0.001	-0.001	0.079	0.310	-0.156
	[0.076]	[-0.249]	[0.869]	[3.806]	[-1.524]
MKT(-1)	0.013	0.001	0.193	0.194	-0.066
	[1.262]	[0.319]	[2.786]	[3.151]	[-0.855]
C	0.236	0.173	0.396	0.140	0.751
	[3.772]	[6.939]	[0.959]	[0.381]	[1.626]
MSUR	0.532	0.021	-1.007	4.422	-10.056
	[1.362]	[0.136]	[-0.391]	[1.927]	[-3.492]
R-squared	0.031	0.087	0.058	0.098	0.092
Adj. R-squared	0.004	0.061	0.031	0.073	0.066

does not seem to provide reasonable explanation to different responses across portfolios.

Table 5: VAR Estimates of Portfolio Returns

	Value	Growth		Value	Growth		Value	Growth
All	-7.695	-11.624	leverage H	-12.294	-10.306	Size B	-8.382	-11.366
	[-2.054]	[-2.734]		[-3.134]	[-1.862]		[-1.430]	[-3.279]
			leverage M	-6.502	-11.877	Size M	-8.078	-12.826
				[-1.813]	[-2.832]		[-2.117]	[-2.816]
			leverage L	-7.220	-12.182	Size S	-5.168	-9.090
				[-1.504]	[-2.218]		[-0.978]	[-1.731]

This table summarizes the impacts of monetary surprise MSUR on different portfolio returns based on estimated VAR regressions. t stats are in brackets

Figure 1 and 2 also show the impulse response of other state variables. To save the space of the paper, I only plot the graph for all growth and value class for comparison. The shocks are extracted by Chloesky decomposition so that they are orthogonal to each other by nature. As the graph shows, the growth group seems to be more sensitive to other factors' shocks. For every one standard deviation shocks, growth stocks tend to shift more than value stocks. This is not surprising, since growth firms are usually young firms whose cash flow gains are projected in the distant future.

2.5 Firm-level Return Responses to Monetary Shock

Having seen the results on portfolio regression, one question people would raise here is: how robust is the result? Since I regress 6 different portfolios individually using the data where the data of Federal Funds future is available, the total number of observations in each regression is only 221. So it is very difficult to obtain any useful statistical inference. Since in portfolio regressions, the slopes for state variables are assumed to be same within each growth and leverage class. Without implementing additional assumption, one can do a pooled regression for each growth and leverage class to increase sample size. To make the results comparable, I write the return equation for each stock as

$$R_{it}^j = \alpha^j + \beta_1^j DIP_{t-1} + \beta_2^j INF_{t-1} + \beta_3^j SMB_{t-1} + \beta_4^j HML_{t-1} + \beta_5^j MKT_{t-1} + \gamma^j MSUR_t + e_i$$

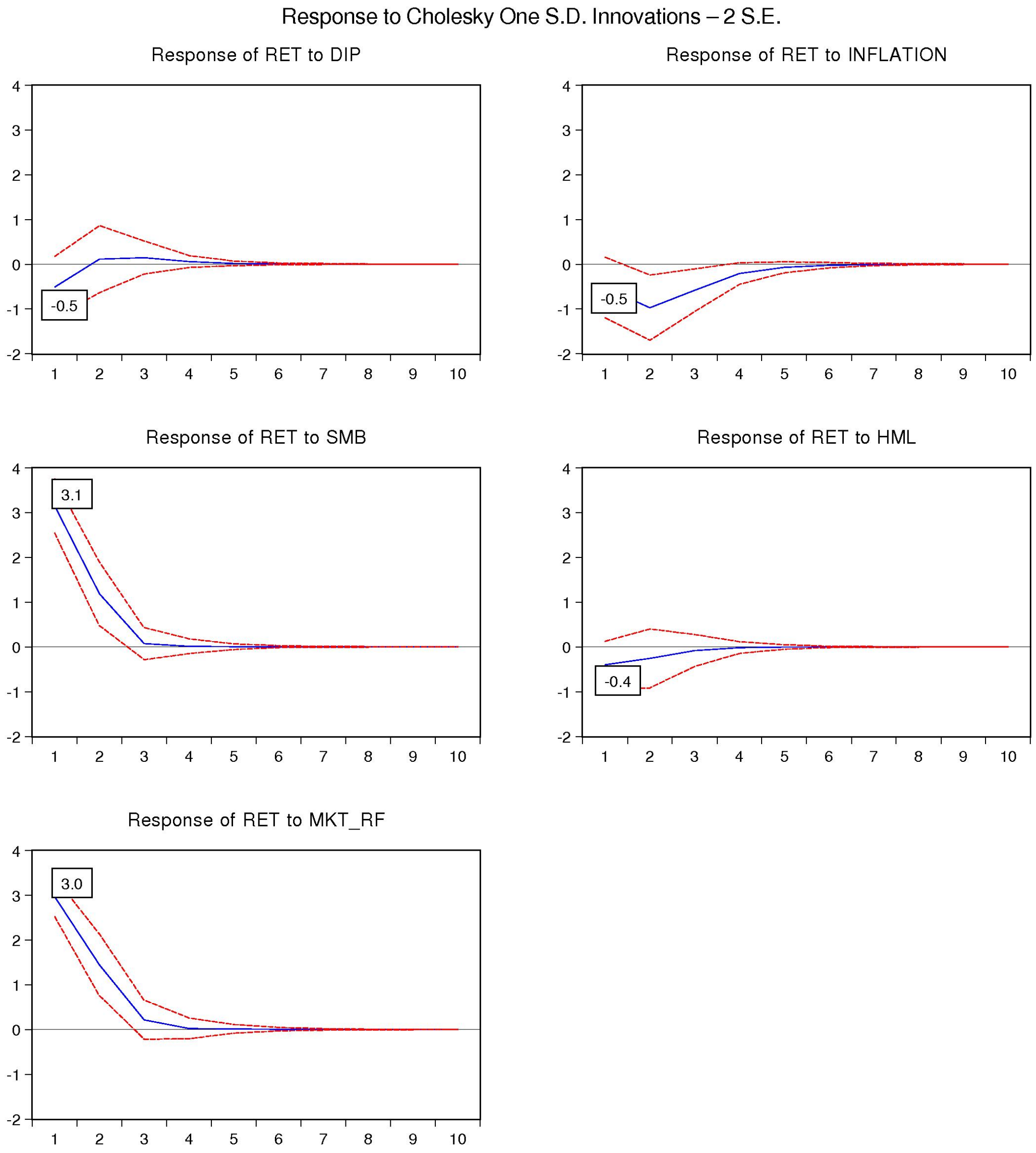

Figure 2.1: Impulse Response of Value Portfolio Return

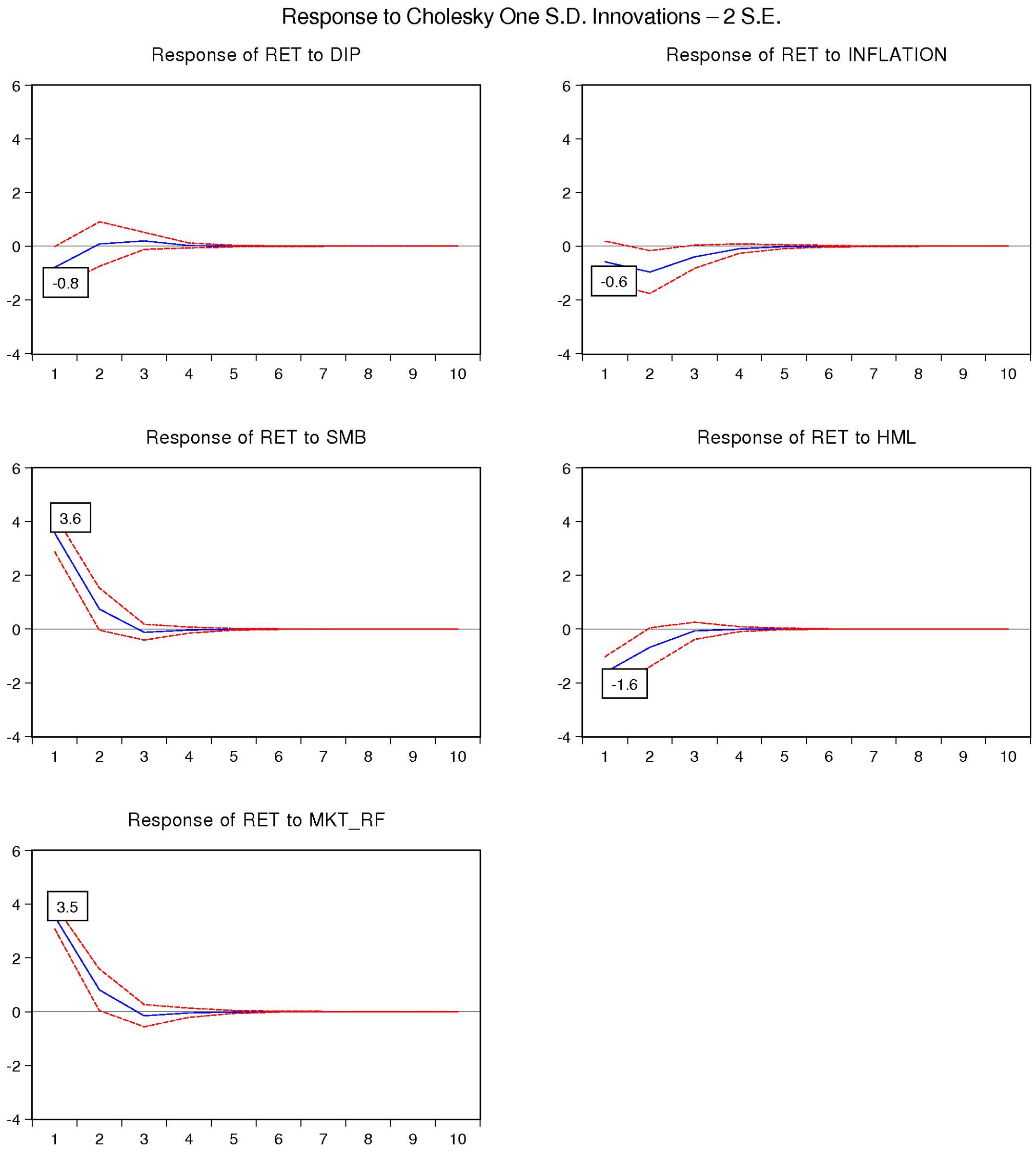

Figure 2.2: Impulse Response of Growth Portfolio Return

Given

$$i \in j \tag{2.13}$$

where subscript i refers to firm i and j refers to different growth-leverage class. Except for monetary surprise, all other state variables are taken in lagged values. For every group, I run a pooled regression and obtain the slope coefficient for each factor. Given that I have a total of 997,314 firm-year observations in my sample, this really adds a lot degrees of freedom to my estimation. However, one caveats have to be noticed here. When doing pooled regression, γ can still be unbiased since it is orthogonal component from monetary shock, while the standard error might be affected by serial correlations of the disturbance terms within the group as pointed by Petersen (2009). To settle this concern, I use the classical Newey-West Regression.

For every month, I first run a cross-section regression for each leverage and book-to-market group. Then I average the estimated coefficients over time and obtain unbiased standard error for each factor loading. The final result is reported in table 6. The predicted signs for monetary surprise are all significantly negative except for those stocks in the value and low leverage group, which is consistent with our VAR estimates. In the value class, likewise, higher leverage creates higher sensitivities to monetary shocks and the difference between high and low leverage class is significant at 95% confidence level. In the growth class, however, the sensitivities to monetary shocks seem decrease with leverage. Moreover, the difference in growth opportunity also provides a reasonable explanation for different responses between growth and value firms, which implies the existence of credit channels in financial markets. Investors view monetary shock as a credit risk to the firm value, depending on its financial health as well as its growth opportunity, the expected future firm value. Although with BGG model alone, it still is not well understood why the relationship between leverage–a proxy for external finance premium and responses to monetary shocks can be opposite for different growth classes. One possible explanation could be that investors have a discretion on the impact of monetary shock and how the external fund is going to be used across firms. If a firm has no good investment opportunity and is highly leveraged, it is more likely to be considered as "financially distressed". When the market credit conditions worsens, higher leverage simply increases its bankruptcy probability. On the other hand, a firm with a good earning prospect is more accessible to various sources of external financing. Therefore, leverage now plays as a signal of private information on how good the project is, rather than a proxy for how likely a growth firm is going to bankrupt. This is consistent with Ross (1977)'s signaling theory of leverage. While my argument is taken from asset pricing and macroeconomic perspective, stock prices respond differently to the same monetary shock due to the fact investors can discern its effects on firms' future values.

2.6 Conclusions

In this paper, I revise the original form of BGG model to allow it to explain cross-sectional features of firms. Based on the theoretical model, I formulate two testable hypotheses. I find that leverage can capture firms' exposure to credit risks. To test if this risk has been incorporated into stock prices, I also investigate stock returns' response to exogenous monetary shocks. Following earlier literature such that Tobin's Q is a reflection of firms' growth opportunity, I use this to segregate my growth and value groups. Both portfolio-level and firm-level regressions indicate there exists a negative relationship between firms' sensitivities to monetary shocks and leverage for growth firms but a positive relationship for value firms. In the value group, most leveraged firms are most sensitive to the shocks while in the growth group, least leveraged firms are most sensitive to the shocks. The fact that highly leveraged growth firms have less monetary exposure might be due to the information content of leverage regarding firms' earning prospect and its mechanism requires further studies.

Table 6: Firm-level Regressions across 6 Growth-Leverage Groups

			Value				
levq	Intercept	Mkt(-1)	SMB(-1)	HML(-1)	INF(-1)	dip(-1)	msur
L	3.153	0.439	0.245	-0.001	-3.433	-0.251	-5.570
	[12.414]	[11.046]	[5.796]	[-0.028]	[-4.528]	[-0.895]	[-3.878]
M	2.223	0.401	0.238	0.096	-2.893	-0.259	-4.799
	[19.648]	[22.536]	[12.674]	[4.143]	[-8.571]	[-2.065]	[-7.469]
H	1.196	0.563	0.282	0.197	-2.315	0.094	-9.365
	[6.134]	[18.401]	[8.706]	[4.946]	[-3.964]	[0.436]	[-8.439]
L-H							3.795
							[2.091]
				Growth			
levq	Intercept	Mkt(-1)	SMB(-1)	HML(-1)	INF(-1)	dip(-1)	msur
L	1.726	0.244	0.092	-0.250	-4.786	0.474	-15.102
	[17.630]	[14.681]	[5.190]	[-11.292]	[-18.015]	[4.345]	[-22.837]
M	1.243	0.213	0.140	-0.079	-3.659	0.470	-13.521
	[24.143]	[25.172]	[15.674]	[-7.046]	[-25.535]	[8.388]	[-41.290]
H	0.814	0.237	0.174	0.102	-3.341	0.701	-11.153
	[10.725]	[18.811]	[13.044]	[6.097]	[-15.927]	[8.430]	[-22.716]
L-H							-3.949
							[-4.794]

This table reports the Newey-West regression by leverage and growth. All state variables except MSUR are taken at lagged values. The coefficients in the table are time average of cross-sectional factor loading estimates over the sample period. t Stats are in brackets.

Chapter 3

Rethink Financial Constraint and Stock Returns-A Return Decomposition Approach

3.1 Introduction

It has been well understood that financial friction is an important factor on real economic activities. Due to information asymmetries, incompleteness of contract, and so on, firms face different costs of raising capital. The term "financial constraint" has been used in the finance literature to describe those firms who have limited ability to raise new fund for all desired investment. Traditional finance theory believes that stock prices reflect the fundamental value of the firms, or the riskiness of the firms' operations, investment and etc. According to this logic, financially constrained firms should yield higher returns on their stock prices since their business performance tend to expose more to aggregate shock of the economy[1].

However, empirical support for this theory seems to be weak. Lamont et al (2001) is the first paper in the literature studying the stock returns on financially constrained firms.

[1]There has been a lot of evidence showing the effect of financial constraint on firms' real activities. For instance, Gertler and Gilchrist (1994) document the "the balanced sheet channel" when studying the performance of US manufacturing firms. Using size as a proxy for the constraints, they find small firms contract more in response to monetary shocks. Similarly, Kashyap et al (1994) study the behavior of inventories investment of manufacturing firms and find that the decline of inventories due to liquidity constraint in recession is correlated with stance of monetary policy.

When forming portfolios based on the KZ index–a common measure of financial constraint introduced by Kaplan and Zingales (1996), they find financially constrained stocks tend to move together but they actually earn lower return than unconstrained counterparts. Furthermore, by taking the cross-sectional return difference between the constrained and the unconstrained as the "financial constrained premium", they are unable to link this premium to any macroeconomic variables or business cycles. Their finding creates a "financial constraint puzzle" since none of the theories in the existing literature can explain the negative sign of the premium.

In this paper, I use a new approach to examine the puzzle. Typical empirical strategy to investigate the premium on financial constraint in the existing literature is to take cross-sectional return difference between constrained and unconstrained groups; this however, always creates insignificant results across groups due to the fact that financial constraint is inevitably correlated with other factors such as size and growth. More importantly, even if one can obtain a significant mimic factor similar to SMB or HML, one still needs an economic interpretation for that factor. Therefore, I adopt the Campbell and Vuolteenaho (2004) two-beta model by estimating cash flow betas and discount rate betas of stock returns individually. This seems to provide a sound theory-based explanation to the reason why there is no significant financial constraint premium observable in the data. It also addresses the economic forces attributable to the common variation of financially (un)constrained stocks as documented by Lamont et al (2001): whether it is cash flow driven or discount rate driven.

Following Lamont's work, many other researchers also work on the topic of financial constraints and pricing of the stocks. Whited and Wu (2006) propose a structural model to identify financial constraint as the shadow price of new funds, and based on the model they derive, they construct a new index (henceforth WW index) to proxy the financial position of the stocks. They find financially constrained stocks actually earn higher return but the difference is insignificant. Similarly, Gomes, Yaron and Zhang (2006) investigate the role of financial friction in an investment-based asset pricing framework. Applying the WW index, they find the most constrained group earn extra .18% monthly returns on average after controlling for size and growth although the premium is insignificant. The groups sorted by the KZ index do not exhibit such cross-sectional difference. Furthermore, Livdan, Horcio and Zhang (2009) introduce aggregate shocks into the model, and their simulated results indicate the existence of common factor among financial constrained stocks and the procyclical pattern of the financial constraint. But again, the premium is insignificant. A recent survey by Campello and Chen (2010) shows a close link of financial constraint with business cycles, credit conditions and so on, but the premium on financial constraint is still negligible.

The puzzle is two-fold: first, why there is no significant return difference across constraint-sorted groups? Second, what drives the comovement within the groups? Financially constrained firms exhibit higher costs of debt and equity and more collateral requirements when seeking external financing, so their return are more susceptible to the shift of the market investment opportunity set. Campbell (1996) shows in the ICAPM's context, this opportunity set can be modeled by the cash flow news of the market index. Therefore, financially constrained stocks become desirable when there is a positive shock on the cash flow news of the market index. On the other hand, the return of stocks can also be affected by their ability to hedge against intertemporal risks. If financially constrained stocks happen to covariate more with the market-level expected future returns or the discount rate, then they are less favorable to investors since by holding them, investor lose more if higher future return on the market index is expected. So with both effects exist in the return dynamic function, investors are not necessarily rewarded with risk premium by holding constrained stocks.

Secondly, what causes financial constrained stocks to move together? Although the existence of the premium is still disputable, earlier literature finds an agreement on the comovement of financially (un)constrained stocks. Various evidence for the comovement can be found in Gomes, Yaron and Zhang (2006), Whited and Wu (2006) and Campello and Chen (2010). The supporters of fundamental view believe any comovement of stock prices is because the cash flows of a specific type of stocks are similar. However, this has been long questioned by behavior finance believers. Laknoishok, Shleifer and Vashiny (1994) keep track the return of growth and value stocks for five years, and they argue higher returns earned on value stocks do not come from the fact that they are riskier but because investors overvalue growth stocks and undervalue value stocks. So the return difference is purely due to higher expectation on future returns of growth stock or higher discount rate that investors apply to the cash flows, rather than future earnings growth. Similarly, the comovement of the (un)constrained can be purely due to investors' sentiment or market frictions. For instance, investors may use a simple rule to categorize stocks, and trade upon it. (I will review this sentiment view in detail in section 2) In sum, the sentiment view argues stocks can still covariate even in the absence of the comovement of cash flows.

Addressing both questions requires the treatment of cash flow and discount rate shocks in stock return separately. To complete this task, I use the decomposition method proposed by Campbell and Vuolteenaho (2004) and Campbell et al (2009). They breakdown the market beta into two parts: cash flow beta, as it captures the portfolio's return covariance with market-level investment opportunity; and discount rate beta, as it captures the portfolio's return covariance with market-level discount rate. As will be discussed more in later section, the comovement of stocks is unlikely to be raised by investors' sentiment through the working of cash flow news (bad beta) since investor's sentiment is independent of (or at least less dependent) firms' and market's fundamentals. For example, if we can find cross-sectional difference in cash flow betas between constrained stocks and unconstrained stocks, then it is unlikely that sentiment is the only reason for comovement. My result indicates that even in the short run, when investors should care more about the change in prices rather than the dividends, financially constrained stocks tend to have higher cash flow beta than the unconstrained ones.

Another thing we can learn from ICAPM or two-beta model is that a conservative long-term investor should care more about changes in cash flow than changes in discount rate news. The reason is because the change of cash flow results in a permanent change of return while the change of discount rate only has transitory effect. If the comovement is cash flow related, then it should not diminish even when investment horizon increases. On the contrary, the comovement of stock returns should echo with the comovement of cash flow news even more. To do this test, I extend the holding periods to 2 years and 5 years so that I can mimic the behavior of long run investors. The importance of cash flow betas on stock returns in relative term is accentuated in the long run, both for constrained and unconstrained firms, and the gap in cash flow betas between the two groups is persistent.

Daniel and Titman (1997) also express a concern that the cross-sectional return differences on characteristic-sorted portfolios merely capture the characteristic that is correlated with return rather than a risk factor. It is possible that the financially (un)constrained firms have similar returns and betas just because they are always similar. To alleviate this concern, I study the comovement of stocks before the year portfolios have been formed. I also use accounting ratios to directly model the cash flow news of both portfolios returns. The pre-formation regression shows that the financial constraint is neither a characteristic that yields spurious results nor a characteristic that has been used irrationally to model comovement, rather it is more likely to be a systematic risk that produces common variations among the stocks that I study.

The results of the paper seem to lend some support for "fundamental risk view" of financial constraint. Of course, readers should always keep in mind when drawing a conclusion on my empirical analysis, I do not rule out the possibility that sentiment plays a role on stock returns.

The paper is organized as follows: section 2 briefly goes over the theoretical basis of sentiment view on comovement and the decomposition procedure proposed by Campbell and Shiller (1988); section 3 presents my cross-sectional results on two-beta models using month-by-month regression; section 4 reports long-run results; section 5 does robustness tests and section 6 concludes.

3.2 Theoretical Review

3.2.1 Sentiment View on Comovement

Barberis et al (2005) argue that in an economy with frictions and irrational investors, stock prices can always deviate from their fundamental values. There are three types of "sentiment-based" comovement according to them.

The first one is category view, which is based on psychological evidence that human beings have the mechanism of grouping things based on similarity. Supposing there are some noise traders who trade based on non-fundamental categories of stocks, or by styles, their trading can raise correlation of those assets in the same style or same class and the return of those assets tend to move together. (ie noise traders take long position on all SP 500 listed stocks) The second type of comovement is due to limited exposure to all available securities, the so-called habitat view. Investors only trade small portion of assets therefore induce a common variation among a specific subset of stocks. The third view is because of the information diffusion. Some stocks respond to new information spontaneously while others not. Therefore, the comovement can be observed after news release such as earnings report. In sum, for whatever the reasons, in the market with frictions, investors are trading stocks based on the grouping that has nothing to do with underlying fundamentals.

Formally, the pricing equation of a stock i's return that belongs to group X can be written as the sum of fundamental shock and sentiment shock such that

$$R_{i,t} = \epsilon_{i,t} + u_{X,t} \tag{3.1}$$

Where $\epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon_i})$ is the shock on dividends or cash flow, $u_{X,t} \sim N(0, \sigma^2_u)$ is the group-specific sentiment shock. Both shocks are orthogonal to each other.

Next, let's see how stocks in category X can covary according to the sentiment view. If one form a portfolio based on the category of X, it is not hard to see that the equal-weighted average portfolio return for X takes the following form

$$R_{X,t} = \epsilon_{X,t} + u_{X,t} = \frac{1}{n}\sum_{i=1}^{n} \epsilon_{i,t} + u_{X,t} \tag{3.2}$$

So if one run single variable regression on the portfolio return such that

$$R_{i,t} = \alpha_i + \beta_i R_{X,t} + v_{i,t}$$

The coefficient β_i is given by

$$\beta_i = \frac{cov(R_{i,t}, R_{X,t})}{V(R_{X,t})} = \frac{cov(\epsilon_{i,t}, \epsilon_{X,t}) + \sigma^2_u}{\sigma^2_{\epsilon_X} + \sigma^2_u} \tag{3.3}$$

Notice that even if we assume $cov(\epsilon_{i,t}, \epsilon_{j,t}) = 0$ for all $i \neq j$, there is still common variation in the stock returns within group X. The beta now becomes

$$\beta_i = \frac{\sigma^2_{\epsilon_i}/n + \sigma^2_u}{\sigma^2_{\epsilon_X} + \sigma^2_u} \tag{3.4}$$

where $\sigma^2_{\epsilon_X} = \frac{1}{n^2}\sum_{i=1}^{n} \epsilon_{i,t}$.

When $n \to \infty$, then it drops to $\beta_i = \frac{\sigma^2_u}{\sigma^2_{\epsilon_X} + \sigma^2_u}$. Therefore, against the fundamental view, the coefficient can still remain significant even in the absence of cash flow similarities among the stocks categorized into the same group.

However, to test their prediction empirically, one encounters a lot of difficulties since stock prices receive both cash flow shocks and sentiment shock from the market. One way to show the effect of sentiment shock (vice versa) is to identify an event or a break point that it can lead to reclassification without changing intrinsic value of the stock itself. Barberis et al (2005) study the component stocks of the SP 500 index and find those stocks tent to produce higher correlation with the SP 500 index after inclusion. They argue the inclusion is not a signal about firms' future cash flow according to the stated goal of Standard and Poors' but an indication of changing market perceptions. However, studying events like this place a lot of limitation on types of empirical studies that researchers can apply to. Therefore, as an alternative, decomposing stock returns can overcome this limitation and allow researchers to directly test fundamental-based comovement versus sentiment-based comovement.

3.2.2 Return Decomposition

The realized holding period return can be expressed in log form such that

$$r_{t+1} = \log(P_{t+1} + D_t) - \log(P_t) \tag{3.5}$$

Using first-order Taylor expansion, Campbell and Shiller (1988) show stock return can be thought of as two linear parts: those of which reflect the change of future stock prices ($N_{DR,t+1}$), and those of which reflect the change of the dividends ($N_{CF,t+1}$). When investors take prediction about return over next period, these two components also reflect the conditional expectations that investors have about future changes. Therefore, the conditional pricing error can be written as

$$\begin{aligned} r_{t+1} - E_t r_{t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= N_{CF,t+1} - N_{DR,t+1} \end{aligned} \tag{3.6}$$

where Δd_t is the dividend growth rate, ρ is a constant parameter defined as $\rho = 1/\exp(\overline{d_t - p_t})$.

Notice this method requires no further specifications of the stock price itself, and it can be applied to any stock return including the market return. In order to decompose market-level returns empirically, Campbell and Vuolteenaho (2004) propose a VAR system with several predictive state variables as well as market return, so that it can take the form such

$$z_{t+1} = \Gamma z_t + u_{t+1} \tag{3.7}$$

where z_{t+1} is a vector such that

$$z_{t+1} = \begin{pmatrix} R_{M,t+1} \\ TY_{t+1} \\ PE_{t+1} \\ VS_{t+1} \end{pmatrix} \tag{3.8}$$

where $R_{M,T+1}$ is the market excess return, TY_{t+1} is the term yield spread defined as difference between long run bond yield and short run bond yield, PE_{t+1} is the price-earning ratio and VS is the value spread, the return difference between small value firms and small growth firms. Since the model can be traced to infinite horizon, combining with equation 3.6, one can obtain discount rate news

$$\begin{aligned} N_{DR,t+1} &= (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= e1' \sum_{j=1}^{\infty} \rho^j \Gamma^j u_{t+1} \\ &= e1' \rho \Gamma (I - \rho\Gamma)^{-1} u_{t+1} \\ &= e1' \lambda u_{t+1} \end{aligned} \tag{3.9}$$

where $e1' = [1, 0, 0, 0]$ and $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$. Following the return identity in 6, cash flow news can be backed out as

$$N_{CF,t+1} = (e1' + e1'\lambda) u_{t+1} \tag{3.10}$$

where $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$.

If one estimates market-level cash flow news and discount rate news in this fashion, then by covarying with individual stock's return, one can break down traditional CAPM's beta into two components. Campbell (1996) derives investor's optimal choice in the intertemporal context such that any individual asset's excess return can be expressed as its covariance with market portfolio's cash flow news and its covariance with market's discount rate news (expected return news).

$$E_t r_{t+1} - r_{f,t+1} = \gamma \sigma_m^2 \beta_{i,CFM} + \sigma_m^2 \beta_{i,DRM} \tag{3.11}$$

where γ is the risk-aversion coefficient from Epstein-Zin utility function (for a conservative investor, $\gamma > 1$), $r_{f,t+1}$ is the risk-free rate, σ_m^2 is the market volatility, $\beta_{i,CFM}$ is the cash flow beta $\beta_{i,CFM} = \dfrac{cov(r_{i,t+1}, N_{CFM,t+1})}{\sigma_m^2}$ and $\beta_{i,DRM}$ is the discount rate beta $\beta_{i,DRM} = \dfrac{cov(r_{i,t+1}, -N_{DRM,t+1})}{\sigma_m^2}$.

This is consistent with Merton's ICAPM's argument: If an asset has higher cash flow beta, then it yields higher return when there is positive shock on market cash flow news since it covariates with improved market investment opportunities; if an asset has high discount rate beta, it becomes more desirable when there is negative shock on market discount rate news since it has higher ability to hedge downward risk.

The two-beta model brings several interesting implications for researcher to understand the relationship between risk and return. First of all, if stocks are priced in this way, then the cross-sectional difference in stock returns or the premium should be attributable to the difference in the betas (either discount rate beta or cash flow beta). Campbell and Vuolteenaho (2004) use this framework to explain the value premium puzzle, and they find the reason that value stocks have higher return is because of higher cash flow betas in value stocks. Second, by distinguishing sources of market shocks, one can better understand the nature of price comovement. As our discussion of financial constraint, if financial constraint is merely a reflection of investors' sentiment, then it should not affect cash flow news of the market return nor the cash flow news of financially constrained stocks. Cash flow news of a firm, after all, is a reflection of the firm's earning ability while the market-wide cash flow news is simply the aggregation of all firms in the market. This fundamental information is less likely to be influenced by market over- or underreaction to the stock prices. Of course, some feedback from market valuation of the firm's stock price can lead to CEOs' decisions regarding how to finance the investment and how to distribute retained earnings, but the mechanism should be rather indirect and limited[2]. Therefore, sentiment cannot induce cross-sectional difference in cash flow betas. The concern that sentiment can work through the channel of cash flow beta can be even alleviated when we use direct proxy rather than VAR backed-out residuals to model cash flow news since we use realized accounting ratios up to 5 years to remove possible valuation bias in stock prices. All these ideal features make two-beta model a sound equipment to test the rationale for financial constraint.

[2]See Baker, Stein and Burgler (2003) for details. They argue equity-dependent firms tend to issue new shares when their stock price is high. This is an example that stock prices affect real earnings by diluting.

The significance of cash flow betas, of course, explains the comovement is cash flow driven while higher level of cash flow betas for constrained stocks can induce the premium. Unlike value premium, it is still doubtable whether the premium associated with financial constraint ever exists. Even in their seminal work on financial constraint, Lamont et al(2001) is unable to identify any monotonic return within KZ-sorted portfolios. What they find is the highest return occurs in the middle-KZ group despite the fact that low-KZ firms by average outperform the high-KZ firms. This creates an issue when one tries to model return using a common mimic factor FC as the return spread between low-KZ firms and high-KZ firms since it fails to explain the abnormal return of middle-KZ group. My cross-sectional regression shows that by implementing two-beta model, it is reasonable to expect higher return occurs in the middle group if investors try to trade off between the impact of cash flow shock and discount rate shock.

3.3 Monthly Results

The data for the entire project come from several different sources. The first part consists of the state variables in the VAR system. Following Campbell and Vuolteenaho (2004), my 4 state variables are value-weighted CRSP return, term yield spread (TY) from Global Financial Data, price earnings ratio (PE) from Shiller's web site, and value spread (VS) constructed from French data library. Since I extend my sample period to year 2010 while Campbell and Vuolteenaho (2004) covers from 1929 to 2001 and TY is no longer available after 2001, I use the yield difference between 10 year constant maturity treasury bond and 1 year bond for the post-2001 data. The rest of my data set is pretty much the same as theirs.

I estimate one-lag VAR to reveal the dynamics of all state variables as shown in table 7. A recent paper by Chen and Zhao (2009) pointed out the limitation of VAR approach to decompose the cash flow news and the discount rate news since the cash flow news is backed out as a residual in the regression. So the result could be sensitive to VAR model specification. While the model selection is critical to the prediction of market return, the purpose of the paper is not to evaluate the performance of the model, but to sort out the sources of financial constraint anomaly using existing estimation strategy. Therefore, whichever model specification is applied, the interpretation of cash flow and discount rate

Table 7: VAR Parameter Estimates of Market Excess Return

	Rm_t	TY_t	PE_t	VS_t	R^2
Rm_{t+1}	0.107***	0.004**	-0.017***	-0.011**	
	(0.032)	(0.002)	(0.005)	(0.005)	
TY_{t+1}	-0.015	0.939***	-0.004	0.049	
	(0.158)	(0.011)	(0.025)	(0.026)	
PE_{t+1}	0.520***	0.001	0.992***	-0.003	
	(0.021)	(0.001)	(0.003)	(0.004)	
VS_{t+1}	-0.022	0.000	-0.002	0.988***	
	(0.032)	(0.002)	(0.005)	(0.005)	

News Covariance and Correlation

Covariance	$N_{CF,t+1}$	$N_{DR,t+1}$	Correlation	$N_{CF,t+1}$	$N_{DR,t+1}$
$N_{CF,t+1}$	0.000673	1.16E-06	$N_{CF,t+1}$	1.000	0.00095
$N_{DR,t+1}$	1.16E-06	0.00224	$N_{DR,t+1}$	0.00095	1.000

The table reports the VAR estimates of market excess return and covariance and correlation matrix of cash flow news and discount rate news. The estimation is based on first-order VAR. Rm is the market excess return, TY is the term yield spread between long run and short run taxable bonds, PE is the log price earnings ratio, VS is the small stock value spread. The sample period covers from 1929:1 to 2010:12. All standard errors are in parenthesis. *** denotes 1% significance level, and ** denotes 5% level.

news should remain unchanged. For robustness check, I also use direct proxy approach to separate return as an alternative, and it turns out that the results are qualitatively similar.

My VAR result is quantitatively similar to those in Campbell and Vuolteenaho (2004) while I have included 10 years' more observations. So this implies that at least the VAR specification is quite consistent over time. Panel B also reports covariance and correlation of estimated cash flow news and discount rate news. And the simple correlation test shows that both shocks are almost orthogonal with correlation of -0.00095, which is a nice property for beta decomposition.

My firm-level data is from CRSP and COMPUSTAT starting from fiscal year of 1964. I exclude the data in starting years of COMPUSTAT since either the accounting ratio needed is incomplete or the number of firms is too few (less than 10) to form a reliable portfolio. To be in my sample, the firm should have at least 3 years of entry in COMPUSTAT for monthly regression and at least 5 years of entry for long run regression. This part of data is then intersected with the subsample of estimated VAR-based news whose estimation period is longer.

Next I proceed with the construction of financial constraint portfolios. A clean and precise proxy for financial constraint is crucial. Earlier studies use size or investment sensitivity to cash flow as a proxy for financial constraint, while these measures are indistinguishable from another risk-related term "financial distress". Many researchers argue that financially constrained firms are not those firms who suffer from possible bankruptcy or liquidation risks; they are generally healthy firms who just seem to be inflexible in "adjusting capital investment to mitigate the impact of aggregate shocks on dividend streams" [3]. Kaplan and Zingales (1997) study a group of manufacturing firms and categorize firm's financial positions into several groups such as "very constrained, unconstrained". Then they chose several relevant "indicators" and run an ordered probit on financial positions of the firms. The estimated coefficients of their original regression are then used to construct the "KZ index". The measure itself makes a clear distinction between "financial constraints" and "financial distress" since it requires the studied firms have positive sales growth.

My KZ index is computed in the same fashion as Lamont et al (2001) such that

$$\begin{aligned} KZ_t = -1.002 \cdot (CF_t/K_{t-1}) + .283 \cdot Q_t + 3.139 \cdot (Debt_t/TotCAP_t) \\ -39.368 \cdot (D_t/K_{t-1}) - 1.315 \cdot (Cash_t/K_{t-1}) \end{aligned} \tag{3.12}$$

where CF_t is the cash flow in year t, computed as sum of COMPUSTAT item 18 and item 14. K_{t-1} is the beginning-of-the-year capital, and is defined as item 8. Q_t is the Tobin's Q, which is the ratio of market value of total assets to book value of total assets. $Debt_t$ is the sum of long-term debt (item 9) and short-term debt (item 34). $TotCAP_t$ is the total liabilities, which is the sum of debt and total equity. D_t is the dividend and $Cash_t$ is the cash holding of the company (item 1). To be consistent with their result, I focus on manufacturing firms only (SIC code from 20-39). This version of the KZ index is a simplified form of their original specification but it accommodates the spirit of the index as well as data availability. I also check the robustness of the result using an alternative

[3]see Lividan, Sapriza and Zhang (2009)

measure in section 5.

After getting the KZ index, market value of equity and book-to-market ratio are also computed following Fama and French (1993). To avoid possible data error, I exclude those firms whose book-to-market ratio is greater than 100 and less than 0.01. All the firms in my sample should have available information mentioned above and this gives me 54,798 firm-year observations. This piece of data provides sufficient accounting information for sorting, and is then merged with CRSP data to form portfolios. For every year t, I form portfolios in June by using the information available by that time. To avoid synchronization problem of fiscal year end and calendar year end, I choose the mid of the year t to rebalance my portfolios and allow at least 6 months gap for market perception of the accounting information. I sort all the stocks according to their KZ index, and the highest 33% of the firms are considered as "financially constrained firms" (marked as C) while the lowest 33% are "financially unconstrained" (marked as U).

Many researchers have also pointed out the importance of controlling confounding effects while studying financial constraint, since these factors are very much likely to be correlated with the existing measure of financial constraint. For instance, Lamont et al (2001) controls the size factor while studying financial constraint and they form 3 by 3 KZ- and size-sorted portfolios. Zhang et al (2006) argue the importance of controlling growth factor also, hence they form a 3 by 3 by 3 KZ-, size and book-to-market sorted portfolios. Campello and Chen (2009) use a different approach such that they assign "scores" to each of 4 one-way characteristics rankings (such as KZ, size, dividend and so on) and they add the scores for each firm and re-rank. My sorting scheme is to intersect my 3 KZ-sorted portfolios with 3 size-sorted portfolios and 3 book-to-market-sorted portfolios, respectively. By doing this, I can form "size-neutral" and "growth-neutral" portfolios for the comparison purpose while still have sufficient number of firms in each portfolio. Moreover, by taking equally-weighted average return from both sorting schemes, I can then form "size- and growth-neutral" portfolios. All the portfolios are formed by equal weighting and sorted independently so this can reduce the return correlation with other known factors.

Table 8: Summary Statistics of Monthly Portfolio Return

Panel A: KZ and Size sorted Portfolios

	Mean	St Dev	Maximum	Minimum
Low KZ (Unconstrained)				
Small Cap	1.563	6.853	35.044	-28.173
Median Cap	1.102	6.651	31.547	-30.897
Big Cap	1.038	5.449	20.356	-27.303
Middle KZ				
Small Cap	1.698	6.546	33.839	-29.144
Median Cap	1.280	6.116	32.358	-29.770
Big Cap	1.053	5.180	20.795	-28.871
High KZ (Constrained)				
Small Cap	1.715	7.368	39.695	-28.515
Median Cap	1.084	6.985	33.557	-35.969
Big Cap	0.952	5.959	21.790	-33.502
SMB (Small Cap-Big Cap)	0.644			
t Statistics	2.889***			
FC1 (High KZ-Low KZ)	0.016			
t Statistics	0.070			

Table 8: Continued

Panel B: KZ and Book-to-Market sorted Portfolios

	Mean	St Dev	Maximum	Minimum
Low KZ (Unconstrained)				
Low Btm	0.908	6.400	29.387	-29.483
Median Btm	1.304	5.965	27.443	-28.409
High Btm	1.599	5.728	31.754	-27.158
Middle KZ				
Low Btm	0.984	6.362	26.477	-30.619
Median Btm	1.255	5.574	28.725	-28.700
High Btm	1.569	5.436	26.598	-29.012
High KZ (Constrained)				
Low Btm	0.955	7.991	33.727	-32.237
Neutral Btm	1.317	6.759	36.307	-32.754
High Btm	1.610	6.154	34.666	-30.345
HML (High Btm-Low Btm)	0.644			
t Statistics	2.834***			
FC2 (High KZ-Low KZ)	0.024			
t Statistics	0.103			

This table reports summary statistics of monthly portfolio returns from 1964:7 to 2008:6. The construction of size and book-to-market classes follows Fama and French (1992, 1993), where the portfolios are rebalanced annually in July. The KZ portfolios are sorted based on annual KZ index where they are available by the construction of the portfolios. The intersection of both size and book-to-market classes with KZ are based on independent sorting. FC1 is the size-stratified premium on financial constraint, taken as monthly return on high KZ- and size-sorted portfolios minus low KZ and size-sorted portfolios. FC2 is the growth-stratified premium. All portfolios are equally weighted.

Table 8 summarizes the monthly returns of two-way sorted portfolios. I report the equal-weighted average monthly return of KZ and size sorted portfolios in panel A and the return of KZ and book-to-market sorted portfolios in panel B. I produce a factor-mimic variable FC1 and FC2 by controlling size effect and growth effect, respectively. FC1 is the return difference between equal-weighted average of three constrained groups and that of three unconstrained groups intersecting with size, such that, $FC1 = \frac{(CS+CM+CB)-(US+UM+UB)}{3}$. While FC2 is $\frac{(CH+CN+CL)-(UH+UN+UL)}{3}$. The first letter denotes the KZ group, Constrained or Unconstrained; and the second letter denotes the size group: Small, Median and Big, or the growth group: High, Neutral and Low. Interestingly, both sorting schemes show that financially constrained stocks have slightly higher return than those unconstrained ones. But the difference is negligible: only .024% for growth sorted and .016% for size sorted. My result is qualitatively equivalent to those found by Campello and Chen (2010), while different from Lamont et al (2001). Also, the pattern is not very monotonic. When sorting on size, the highest return occurs in the middle KZ group, with average return of 1.34%. By simply comparing the return difference across KZ groups, the puzzle is not solved.

Next I proceed to show the monthly regression results on market shocks. Following Campbell and Vuolteenaho (2004), I also include one lag of market news to alleviate the concern on non-synchronization of stock return data (ie some stocks are not traded frequently and their return data can be delayed). Therefore, my estimated cash flow beta is actually

$$\widehat{\beta_{i,CFM}} = \frac{cov(r_{i,t}, \widehat{N_{CF,t}}) + cov(r_{i,t}, \widehat{N_{CF,t-1}})}{Var(r_m)} \tag{3.13}$$

and the discount rate beta is

$$\widehat{\beta_{i,DRM}} = \frac{cov(r_{i,t}, -\widehat{N_{DR,t}}) + cov(r_{i,t}, -\widehat{N_{DR,t-1}})}{Var(r_m)} \tag{3.14}$$

Table 9 shows cash flow and discount betas based on monthly regressions. Obviously, in monthly investment horizon, the importance of discount rate news outweighs that of cash flow news for all the 18 portfolios. This is not surprising though since short-run investors are most likely to be noise traders or speculators so their risk aversion is relatively lower (as $\gamma < 1$ in equation 3.11). They care more about the change of price in a given time horizon rather than terminal value of the assets or the flow of dividends. Panel A gives the regression results for size and KZ sorted portfolios and panel B gives the results for book-to-market sorted portfolios. The last rows of both tables take differences in betas across KZ groups. One thing worth attention in the table is that when moving from low-KZ to high-KZ groups, one can see an increasing trend in both betas. And all the numbers in Diff rows are positive, showing constrained stocks have higher cash flow betas and higher discount rate betas although not all of those differences are statistically significant. In panel C, portfolio returns are constructed by controlling both size and growth effects. For instance, the returns on constrained size- and growth- neutral portfolio is the equal-weighted average of 6 high KZ groups such that $R_c = (CS + CM + CB + CH + CN + CL)/6$. Unlike the differences shown in panel A and B, it measures overall effect of financial constraints on stock returns. The difference shows that constrained stocks exceed unconstrained stocks by .208 in cash flow betas.

The test of two-beta models can also be extended in a purely time-series context by use of FC, the spread between constrained and unconstrained. In this test, I follow my previous implementation of size and growth- neutral portfolios. And the spread is computed as $FC = ((CS+CM+CB+CL+CN+CH)-(US+UM+UB+UL+UN+UH))/6$. Combining with known factors, one can now identify the sources of the premium. The logic is simple, if the premium is all due to those known factors, then the constant term on the regression, so called alpha should be insignificant. Four specifications have been tried here: Fama-French 3 Factor, Fama-French 3 Factor plus momentum, two-beta CAPM, two-beta CAPM with lags and momentum. Table 10 shows that despite Fama-French 3 factors (market, size and book-to-market) can partially explain the premium (since they are correlated with the constraint factor inevitably); it seems that the premium has a source that is independent of those existing factors. Because the premium has been constructed such that it is neutral to size and growth, the significance of alpha on the first two regressions reflects the underlying characteristics other than size and growth. The first two regressions have both positive and significant factor loadings on SMB and HML, implying small firms and value firms are more likely to be financially constrained. I include the momentum factor to model underreaction, but it is insignificant. Moreover, when I use the two-beta model, the alpha becomes insignificant showing the enhanced explanatory power of the model as opposed to other candidate specifications. The insignificance of the alpha also implies the premium is mainly captured by the differences in betas, that is, financial constrained firms tend to have both higher cash flow betas and discount rate betas and they are unambiguously riskier than unconstrained ones.

The monthly regression also more or less sheds the light on why there is no obvious premium observed in monthly returns. Notice that by construction, the cash flow news and discount rate news drive stock return into opposite directions. One unit of positive cash flow shock leads to an increase of return by $\beta_{i,CFM} \times 1$, while one unit of positive discount cash flow shock leads to a decline by $\beta_{i,DRM} \times 1$. As a numerical example, if one takes a long position on constrained stocks and a short position on unconstrained stocks, the overall impact on 1% upward market movement is virtually small: it is only (0.208-0.099)*1%=0.109% per month.

3.4 Long-run Results

In this section, I investigate the long run comovement of financially (un)constrained stocks. The base line for return decomposition or return predictability, is that dividend growth is unpredictable while dividend price ratio is quite persistent. Therefore, any shock on expected return or discount rate can only lead to temporary movement of the stock prices if the dividend remains fixed; while a shock on dividend growth can cause permanent revision of stock prices. That also explains that a long run investor whose risk aversion γ is greater than 1, places higher weights on cash flow news while valuing stocks. To see this, I use Cochrane (2005)'s framework to briefly derive the result. Assuming that the market-level log return depends on one state variable x_t for simplicity, and the dividend growth is controlled by an unforeseeable white noise ϵ_t, so we have

$$x_t = bx_{t-1} + \delta_t \tag{3.15}$$

$$r_{m,t+1} = x_t + \epsilon_{r,t+1} \tag{3.16}$$

$$\Delta d_{t+1} = \epsilon_{d,t+1} \tag{3.17}$$

Solving through 14 to 16, we can have cash flow news $N_{CF,t+1} = \epsilon_{d,t+1}$ and discount rate news $N_{DR,t+1} = \dfrac{\delta_{t+1}}{1-\rho b}$.

If one holds an asset for more than one period, then his k's holding period return can be approximated by the sum of k periods log returns

$$r^k_{i,t+1} \approx \sum_{j=1}^{k} r_{i,t+j} \tag{3.18}$$

and accordingly we can redefine multiple-period news in the following form

$$N^k_{CF,t+1} = \sum_{j=1}^{k} N_{CF,t+1} \tag{3.19}$$

$$N^k_{DR,t+1} = \sum_{j=1}^{k} N_{DR,t+1} \tag{3.20}$$

Also given that individual asset return $r_{i,t+j}$ is affected by the shocks from both news

$$r_{i,t+1} = \lambda_{CF} N_{CF,t+1} + \lambda_{DR} N_{DR,t+1} \tag{3.21}$$

the long-run cash flow beta over k's period is then

$$\beta_{i,CFM}^{k} = cov(r_{i,t+1}^{k}, N_{CF,t+1}^{k})/Var(r_{m,t+1}^{k}) = \lambda_{CF} \cdot \frac{Var(N_{CF,t+1}^{k})}{Var(r_{m,t+1}^{k})} \tag{3.22}$$

and the long-run discount rate beta over k's period is

$$\beta_{i,DRM}^{k} = cov(r_{i,t+1}^{k}, N_{DR,t+1}^{k})/Var(r_{m,t+1}^{k}) = \lambda_{DR} \cdot \frac{Var(N_{DR,t+1}^{k})}{Var(r_{m,t+1}^{k})} \tag{3.23}$$

Hence the relative importance of betas is driven by the variance ratio of the news. Chen and Zhao (2009) shows the variance of market return over k period can be expressed as

$$Var(r_{m,t+1}^{k}) = (\sum_{i=1}^{k} r_{m,t+i}) = kVar(\epsilon_d) + \sum_{i=1}^{k} (\frac{\rho}{1-\rho b} - \frac{1-b^{k-i}}{1-b})^2 Var(\delta) \tag{3.24}$$

With $b < 1$, it is not hard to see as the investment horizon k increases, the proportion of dividend or cash flow variance in total market variance increases, implying strengthening explanatory power of cash flow beta; while the proportion of discount rate or expected return news diminishes, implying weakening explanatory power of discount rate beta. If financial constraint is rationally priced and creates no sentiment bias in dividend growth path, as the equation shows, discount rate beta will ultimately be dominated by cash flow beta for very long investment horizon. On the other hand, if financial constraint is purely sentimental, then it could be the case that discount rate news always dominate. Thus, the comovement of financially constrained stocks are due to the similarity in the response to market-wide discount rate news. [4]

In order to test this hypothesis, I try two investment horizons: 2 years and 5 years. To mostly mimic the behavior of long run investor, I assume the investor apply buy-and-hold strategy for n years, and during that period he does nothing such as rebalancing his portfolio or reinvesting with his dividends. Nor the investor are allowed to sell his position in the middle of holding period. If the firm is delisted in his portfolio during

[4] See Shleifer and Vishny (1998) for details. They show stock price as sum of a random walk component of dividend growth and a deviation from the firm's fundamental value. The reason mispricing can exist for a very long horizon is because people forecast dividends using regime-switching probability while the true process is random walk. This causes stock prices' continuous deviations from the fundamental values even if there is a prolonged investment horizon.

the holding period, I simply treat the return as zero. So the holding period return is the gross return over 2 years' or 5 years' period. To avoid losing too much degree of freedom in estimation, I employ a strategy of forming overlapping portfolios. In every month j in year t, 9 size and KZ sorted portfolios as well as 9 book-to-market and KZ sorted portfolios are formed based on available accounting information by month j. And then the return is cumulated until month j-1 in year t+2 or t+5 to match desirable investment horizons. During that time, the components of each portfolio are fixed. Then I obtain the 2- or 5-year return of each portfolio and match with corresponding market news of the same period. The strategy is similar to rolling regression except for the forward-looking mechanism as opposed to backward-looking in rolling regression.

Table 11 presents the regression results of 2-year and 5-year investment together. Comparing with monthly regression, both magnitude and significance of discount rate betas diminishes. For instance, there is no single estimate of discount rate beta greater than 1 while in monthly regression, all the discount rate betas are greater than 1. The same story can be found for the declining significance. At 5 years horizon, 5 out of 18 portfolios have insignificant estimates of discount rate betas while in monthly regression, all the discount rate betas are highly significant. In contrast, most cash flow betas still remain highly significant for both 2 year and 5 year horizons. In every panel, I also report the regression coefficients on size-and growth-neutral portfolios. The difference in cash flow betas between the constrained and the unconstrained follows the same pattern as in monthly regressions, however, the discount rate betas are now larger for low-KZ groups in contrast to monthly regressions. The overall difference is -.164 for 2-year and -.203 for 5-year, and both are statistically significant. The adjusted financial constraint premium FC is still insignificant although it improves from monthly results.

Other unexpected results from the table are also noteworthy. When the investment has been extended to 5 years, the sign of the discount rate betas change. For instance, the coefficient on median-sized and constrained stocks have a negative slope of -.150 and it is statistical significant. The reason for the reversal of the signs is complex. Firstly, it could be due to poor fitting of log return. Logarithm provides a sound approximation for holding period return when the change of price is not very large. When investment year accumulates, the errors generated by mismatch escalate. Secondly, the VAR I implement to produce news terms are based on monthly data. So by nature, they are different in the way how expectations are formed. Monthly data can contain too much noise hence lower the predictive power. But even if I switch to long-run market data that is the same with the investment horizons (say biannual data for VAR regression), it can still be inconsistent with the portfolios' holding periods since the holding period is inevitable overlapping with portfolio formation year. Thirdly, when extending to 5 years, my data inevitably suffers from survival bias. Cohen, Polk and Vuolteenaho (2009) also give the warning on placing too much weight on longer horizon. While we want to model the long run investor behavior as much as possible, the limitation of the data and the statistical inference problem makes the mission rather difficult.

Lastly, but also most importantly, it is regarding how we can interpret discount rate betas. As table 11 almost gives unanimous fact that unconstrained stocks have higher discount rate beta, the understanding of information content of discount rate beta is important. Unlike the cash flow news beta which is almost certainly driven by the fundamentals, the discount rate beta can be affected by both investors' sentiment and the fundamentals. Campbell and Vuolteenaho (2004) provide some "rational" explanations for high discount rate betas such as booming investment opportunity, longer duration of cash flow and higher dependence to external financing. If a financially constrained firm is believed to have difficulty of changing its current financial position, then it is expected to receive net positive cash flow from a distant future. In such a circumstance with long duration of cash flow, the market-wide discount rate shock such as change of short-run rate, leads to smaller change of the firm's equity value than the unconstrained since its demand for short-term debt is restricted by its current financial positions. Why didn't we see the pattern in monthly data? It could be due to the fact that the fundamental component in discount rate news only looms in conservative long-run investors' pricing function. Of course, it is also possible that this phenomenon is purely sentiment driven.

3.5 Robustness Checks

3.5.1 Switchers and Stayers

In this section, I test whether the empirical results we have seen so far are just characteristic-associated phenomena rather than fundamental risks. Daniel and Titman (1997) argues that the return premium on characteristic-sorted portfolios merely captures the characteristic that is correlated with return rather than the risk factor itself. A characteristic can induce stock return comovement due to many reasons, and the source of its effect is attributable to two perspectives. A characteristic can mean some similarities across firms such as firms are in the same industry or the same region but this characteristic does not require corresponding risk charge on its loading. When sorting on such characteristic, stock returns for the firms in the same group move together not because they share the same risk features, but because they are similar firms. In other words, if one tracks those firms who are categorized in the same characteristic-sorted group in year t backwards or forwards, those stocks are likely to covary even as they are not in the same group.

To show that financial constraint is not a characteristic producing spurious statistical results, I follow Lamont et al's (2001) approach. I first sort all the firms in my sample according to their KZ index in July every year t. Then I track the components of each KZ group up to 5 years prior the sorting year. If they are different from what it is now, they are "switchers"; and if they remain in the same KZ sorted group, they are "stayers". Within the group of switchers, there are two subgroups: those who switch from higher KZ to low KZ (unconstrained by the year t) and those who switch from lower KZ to high KZ (constrained by the year t). A portfolio is then constructed by taking a long position in constrained "switchers" and a position in unconstrained "switchers", denoted as FC_{SW}. Similarly, among "stayers", there are "constrained stayers" and "unconstrained stayers", denoted as FC_{ST}. I also construct a benchmark portfolio, with a long position in constrained stocks sorting in every year and a short position in unconstrained stocks. The return is taken from my size- and growth- stratified portfolios FC mentioned earlier. Intuitively, stayers should have similar correlations with the benchmark throughout our 6 years' event window since their rankings are fixed regardless which theory is true. For switchers, if their correlations remain alike given their changing rankings from t-5 to t, then it supports the characteristic-based financial constraint theory. The data is monthly data and the sample period is same as my monthly regression from 1964:07 to 2008:06.

Table 12 reports the similar findings by Lamont et al (2001). In panel A, both standard deviation of monthly return FC_{SW} shows an increasing pattern as the sorting year approaches. The correlations with the benchmark and with the stayers increase from 0.149 to 0.378 and 0.009 to 0.213, respectively. Notice that the stayers are a subgroup of

FC, so it is not surprise to see its standard deviation is quite constant over time.

Panel B of table 12 gives a regression-based result on how correlation changes during preformation years. Three univariate regressions are run and every two columns gives estimated coefficients on independent variables as well as R^2. From the left to the right, these are

$$R_{stayer,t} = a + \beta_t R_{FC} + \epsilon_t \tag{3.25}$$

$$R_{switcher,t} = a + \beta_t R_{FC} + \epsilon_t \tag{3.26}$$

$$R_{switcher,t} = a + \beta_t R_{stayer,t} + \epsilon_t \tag{3.27}$$

Again, the coefficients of FC_{ST} are quite constant, yielding insignificant difference between t-5 and t, while the coefficients of FC_{SW} increase dramatically in the formation year. Moreover, the R^2s also rise as an evidence of improved explanatory power of the independent variables. This reassures the finding in panel A, the comovement is strengthened when more switchers are included in the target KZ groups.

One thing that has not been answered in Lamont et al (2001)'s paper is what causes the comovement to reinforce in the sorting year. As it has been shown in the very beginning of the paper, comovement can also occur because of sentiment. Barberis et al (2005) shows that reclassification can lead to increased correlation even though this reclassification is not cash flow driven. To see this, we can follow the derivation in section 3.1, and introduce another group Y. For any stocks in group Y, its return is determined by

$$R_{i,t} = \epsilon_{i,t} + u_{Y,t} \tag{3.28}$$

While the equal-weighted return of group Y is given as

$$R_{Y,t} = \epsilon_{Y,t} + u_{Y,t} = \frac{1}{n}\sum_{i=1}^{n} \epsilon_{i,t} + u_{Y,t} \tag{3.29}$$

And assuming the sentiment shocks $u_{X,t}$ and $u_{Y,t}$ are weakly correlated with the unanimous variance of σ_u^2 and correlation coefficient of ρ, then a switcher k who is originally in X and then reclassified into Y can be regressed on $R_{Y,t}$ with estimated OLS slope equals to

$$\beta_k = \frac{\rho\sigma_u^2}{\sigma_{\epsilon_Y}^2 + \sigma_u^2} \tag{3.30}$$

before reclassification to Y and

$$\beta_k = \frac{\sigma_u^2}{\sigma_{\epsilon_Y}^2 + \sigma_u^2} \tag{3.31}$$

after reclassification if one assumes zero correlation in dividends shocks. Clearly, the slope increases.

So to see if it is mainly driven by sentiment, one has to control the cash flow of stock returns when evaluating the comovement. I develop two ways to test this hypothesis. First, I directly model the cash flow news of stocks by using accounting ratios and check to see if the increased correlation in stock returns is companied by increased correlation in cash flows. The starting point of this method is the clean-surplus accounting identity such that

$$X_t = BE_t - BE_{t-1} + D_t \tag{3.32}$$

Vuolteenaho (2002) shows that there is an approximate linear relation among log return of the stock r_t, the log ROE roe_t and log book-to-market ratio θ_t if one writes

$$\begin{aligned} r_t &= log(1 + \frac{ME_t - ME_{t-1} + D_t}{ME_{t-1}}) \\ roe_t &= log(1 + \frac{BE_t - BE_{t-1} + D_t}{BE_{t-1}}) \\ \theta_t &= log(ME_t/BE_t) \end{aligned} \tag{3.33}$$

By taking first-order Taylor expansion and solving equation 3.33 iteratively, Vuolteenaho (2002) shows the log book-to-market ratio can be expressed as the infinite sum of future accounting earnings minus infinite sum of future returns such that

$$\theta_{t-1} = k_{t-1} + \sum_{j=0}^{\infty} \rho^j roe_{t+j} - \sum_{j=1}^{\infty} \rho^j r_{t+j} \tag{3.34}$$

where k_{t-1} is the approximate error. The components of $\sum_{j=0}^{\infty} \rho^j roe$ naturally becomes cash flow news since it is directly substituted from dividend growth equation. Therefore, using accounting ratio of ROE, one can obtain cash flow as

$$N_{i,CF,t} = \sum_{j=0}^{\infty} \rho^j roe_{i,t+j} \tag{3.35}$$

Notice direct proxy approach model the cash flow itself rather than the expectation error of the cash flow as in Campbell and Shiller although they are basically the same if one assume random walk of the dividend growth. The advantage of direct proxy approach has been stressed by many researchers, as it is seldom affected by the model specification of expected stock returns.

To put this theory into empirical testing, I trace the portfolio-level cash flow news up to 5 years, so I get

$$N_{i,CF,t} = \sum_{j=0}^{4} \rho^j roe_{i,t+j} \tag{3.36}$$

where $\rho = .975$. I extract cash flow for switchers FC_SW, stayers FC_ST and the benchmark portfolios FC as well. Then I put them in the univariate regressions as in Panel B of table 12. The results are displayed in table 13.

As one can see from table 13, both cash flow correlations and regression coefficients demonstrate an increasing trend in line with those patterns observed in the returns. In addition to the use of 5 year summation, I also test the interaction of the current ROE between switchers and stayers. Since the accounting data are only available at yearly basis, my sample size shrinks dramatically. But even so, the estimates on stayers' and FC's cash flow news are good enough to draw statistical inference about it. As it shows in the last two columns of table 13, the slope on stayers' cash flow increases from 0.190 to 0.767 in the observation window, and the slope on the benchmark increases even more-by 0.721 from t-5 to t.

My second strategy is to estimate two betas of switchers and stayers by using monthly returns of the portfolios. Table 8 explores the possibility that the switcher and stayer portfolio can be explained by two-beta model. The portfolios are still long and short style, so the returns are measured as the spreads between constrained and unconstrained. Both cash flow and discount rate betas of stayers are all significant and quite constant throughout preformation years with cash flow betas ranging from 0.577 to 0.755 and discount rate betas ranging from 0.155 to 0.300. Comparing with our result in table 4 model 4, it is very similar to the benchmark premium FC. The result of switchers is also as what we expect. Insignificant through t-5 to t-3, the cash flow betas of switchers are much more volatile than the stayers'. This is because the stocks in switcher portfolio can be different from time to time, the artificially aggregated portfolio has messy ordering in terms of KZ index (ie in some years, one might take long position on both constrained firms and unconstrained for the time being). So due to this random ranking in switcher portfolios, the common variation with respect to financial constraint disappears prior formation years (from t-5 to t-1). After portfolio is rebalanced in year t, the cash flow beta of switcher is 0.253, which increase by .364 from the starting of the window. As been discussed earlier, the cash flow beta captures the fundamental similarity among sorted firms, hence the evolution of cash flow betas of the switchers reveals a gradual converging process of cash flow comovement of the switchers.

3.5.2 Portfolio Sorting using an Alternative Financial Constraint Measure

Whited and Wu (2006) point out some fallacies in the KZ index, such as using Tobin's Q as one of key variables, which can be very noisy in measurement. So they develop a new measure (henceforth WW index) by implementing a structural form of external financial constraint from the investment Euler equation. They derive the measure as the shadow price of gaining external finance, which can be estimated using GMM. The parametric form of the WW index is the following

$$\begin{aligned} WW = -0.091 \cdot CF_{it} - 0.062 \cdot DIVPOS_{it} + 0.021 \cdot TLTD_{it} \\ -0.044 \cdot LNTA_{it} + 0.102 \cdot ISG_{it} - 0.035 \cdot SG_{it} \end{aligned} \tag{3.37}$$

where CF is the ratio of cash flow to total assets; $DIVPOS$ is an indicator that takes the value of one if the firm pays cash dividends; $TLTD$ is the ratio of the long-term debt to total assets; $LNTA$ is the natural log of total assets, ISG is the firm's 3-digit industry sales growth; SG is firm sales growth. The higher the WW, the more constrained the firm is.

After getting WW index, I form WW portfolios and intersect with size and growth portfolios as I did in section 3.3. Then I regress each portfolio's return on market-wide cash flow news and discount news. The result is reported in table 15. It seems that my estimation is independent of the financial constraint proxy I choose, so the previous conclusion that financial constrained stocks have higher cash flow betas and discount rate betas still holds in monthly regression.

3.6 Conclusion

In this paper, I offer a possible explanation to the financial constraint puzzle. This puzzle is actually two-fold: first, is there an identifiable premium associated with financial positions of the firms? Second, why do financially constrained stocks move together? For the first question, like most finding in previous literature, I am unable to find a significant return difference between most constrained firms and most unconstrained firms. By using Campbell and Vuolteenaho's two-beta model, I offer a somewhat new insight to this issue. Financial constrained stocks are more sensitive to both market-wide cash flow news and discount rate news in my monthly regression, therefore, the sign of the premium depends critically on which shock dominates since both betas remain highly significant in the regression.

Furthermore, using the two-beta model framework, the picture regarding how financially constrained stocks covary becomes much clearer. By carefully setting up my hypotheses and designing my experiments, I find the comovement is cash flow driven since almost all KZ-sorted portfolios have significant cash flow betas in both short-run and long-run horizon. Consistent with ICAPM theory, the discrepancy in cash flow betas between unconstrained and constrained is significant, implying constrained firms are exposed more to the shift of market investment opportunity. The result is independent of what proxy is used for financial constraint. The preformation study of switchers and stayers confirms that re-categorizing according to firms' financial constraint status is mainly cash flow driven.

Finally, my work can be viewed as an extension of Campbell and Vuolteenaho (2004) and Campbell, Polk and Vuolteenaho (2009). Like theirs, I cannot reject the existence of sentiment effect and its magnitude towards stock prices while the effect of fundamental is well established and observed. One of few directions for further research will be on the further decomposition or thorough understanding of the information content of discount rate news.

Table 9: Cash Flow and Discount Rate Betas of Monthly Portfolio Return Regression

Panel A: Monthly Regression on Size and KZ sorted portfolios

	Small Cap		Median Cap		Big Cap		Diff (S-B)	
	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$
Low KZ (Unconstrained)	**1.298**	**0.760**	**1.398**	**0.612**	**1.165**	**0.355**	0.133	**0.405**
	(0.067)	(0.097)	(0.054)	(0.078)	(0.032)	(0.047)	(0.082)	(0.127)
Middle KZ	**1.242**	**0.790**	**1.276**	**0.649**	**1.102**	**0.469**	0.140	**0.321**
	(0.062)	(0.090)	(0.047)	(0.068)	(0.029)	(0.042)	(0.075)	(0.117)
High KZ (Constrained)	**1.382**	**0.966**	**1.452**	**0.718**	**1.199**	**0.596**	**0.183**	**0.371**
	(0.072)	(0.105)	(0.056)	(0.080)	(0.039)	(0.056)	(0.092)	(0.139)
Diff(C-U)	0.084	0.207	0.054	0.106	0.034	**0.241**		
	(0.099)	(0.143)	(0.078)	(0.112)	(0.050)	(0.073)		

Panel B: Monthly Regression on Book-to-Market and KZ sorted portfolios

	Low Btm		Neutral Btm		High Btm		Diff (L-H)	
	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$
Low KZ (Unconstrained)	**1.372**	**0.475**	**1.268**	**0.619**	**1.116**	**0.611**	**0.256**	-0.136
	(0.046)	(0.066)	(0.046)	(0.066)	(0.052)	(0.075)	(0.069)	(0.100)
Middle KZ	**1.371**	**0.595**	**1.192**	**0.632**	**1.077**	**0.616**	**0.294**	-0.022
	(0.043)	(0.062)	(0.037)	(0.054)	(0.045)	(0.065)	(0.062)	(0.090)
High KZ (Constrained)	**1.632**	**0.787**	**1.345**	**0.806**	**1.203**	**0.808**	**0.429**	-0.021
	(0.069)	(0.100)	(0.057)	(0.082)	(0.054)	(0.079)	(0.088)	(0.127)
Diff(C-U)	**0.261**	**0.312**	0.077	0.187	0.087	0.197		
	(0.083)	(0.120)	(0.073)	(0.106)	(0.075)	(0.109)		

Panel C: Monthly Regression on Size- and Growth- Neutralized Portfolios

	$\beta_{i,DRM}$	$\beta_{i,CFM}$	R_i in %
Low KZ (Unconstrained)	**1.270**	**0.572**	**1.250**
	(0.045)	(0.065)	(0.258)
Middle KZ	**1.210**	**0.625**	**1.310**
	(0.039)	(0.057)	(0.246)
High KZ (Constrained)	**1.369**	**0.780**	**1.270**
	(0.052)	(0.075)	(0.287)
Diff (C-U)	0.099	**0.208**	0.020
	(0.069)	(0.099)	(0.4)

This table shows the cross-sectional cash flow and discount betas of KZ-, size and book-to-market sorted portfolios. One lag of the market news is included also to alleviate the nonsynchronization issues pointed by Campbell and Vuoulteenaho (2004). Hence the cash flow beta is $\frac{cov(r_{i,t},\widehat{N_{CF,t}})+cov(r_{i,t},\widehat{N_{CF,t-1}})}{Var(r_m)}$ and the discount rate beta is $\frac{cov(r_{i,t},-\widehat{N_{DR,t}})+cov(r_{i,t},-\widehat{N_{DR,t-1}})}{Var(r_m)}$. The last row reports the difference of betas between constrained and unconstrained size or growth controlled portfolios. Panel C reports the two-beta estimation for size and growth-neutralized portfolios. It also gives average monthly returns in percent for KZ sorted portfolios. All standard errors are in parenthesis. The bold font indicates significance level of 5%.

Table 10: Time Series Regression on Financial Constraint Premium FC

	Constant	R_me	SMB	HML	Mom	dsn	cfn	ldsn	lcfn	R^2
MODEL1	-0.214**	0.144***	0.178***	0.307***						21.8%
	(0.085)	(0.021)	(0.027)	(0.032)						
MODEL2	-0.237***	0.147***	0.177***	0.313***	0.022					21.9%
	(0.088)	(0.021)	(0.027)	(0.032)	(0.021)					
MODEL3	0.027					0.065***	0.192***			4.30%
	(0.092)					(0.022)	(0.042)			
MODEL4	0.029				0.005	0.061***	0.222***	0.045**	0.163***	6.73%
	(0.092)				(0.022)	(0.022)	(0.044)	(0.220)	(4.319)	

The time series regression is based on monthly data from 1964:7 to 2008:6. The dependent variable, financial constraint premium FC is the monthly return difference between constrained stocks and unconstrained stocks, computed as $\frac{(CS+CM+CB+CL+CN+CH)-(US+UM+UB+UL+UN+UH)}{6}$. Where C denotes high KZ stocks and U denotes low KZ stocks. For each KZ sorted group, it intersects with 3 size classes (Small, Median, Big) and 3 growth classes (Low, Neutral, High). R_me is market excess return, SMB is factor-mimic return for size, HML is factor-mimic return for book-to-market ratio, and MOM is factor-mimic return for momentum. All these variables are from French data library. dsn and $ldsn$ is market discount rate news and one lag of market discount rate news from my VAR estimation, respectively. cfn and $lcfn$ is market cash flow news and its lag, respectively. All standard errors are in parenthesis. *** denotes 1% significance level, and ** denotes 5% level.

Table 11: Long-run Regressions

Panel A: Discount Rate and Cash Flow Betas of 2-year Returns

	$\beta_{i,DRM}$				$\beta_{i,CFM}$			
	Low KZ	Middle KZ	High KZ	diff	Low KZ	Middle KZ	High KZ	diff
Small	**0.302**	**0.214**	**0.256**	-0.046	**0.519**	**0.461**	**0.631**	**0.111**
	(0.052)	(0.055)	(0.055)	(0.075)	(0.040)	(0.043)	(0.042)	(0.058)
Median	**0.370**	**0.302**	0.051	**-0.319**	**0.409**	**0.363**	**0.443**	0.034
	(0.045)	(0.042)	(0.047)	(0.065)	(0.035)	(0.032)	(0.036)	(0.050)
Big	**0.492**	**0.352**	**0.233**	**-0.259**	**0.108**	**0.142**	**0.249**	**0.141**
	(0.030)	(0.031)	(0.034)	(0.045)	(0.023)	(0.024)	(0.026)	(0.035)
Low	**0.565**	**0.588**	**0.505**	-0.059	**0.222**	**0.261**	**0.335**	**0.113**
	(0.037)	(0.041)	(0.056)	(0.068)	(0.029)	(0.032)	(0.043)	(0.052)
Neutral	**0.313**	**0.272**	0.087	**-0.226**	**0.339**	**0.286**	**0.440**	**0.101**
	(0.040)	(0.034)	(0.048)	(0.062)	(0.031)	(0.026)	(0.037)	(0.048)
High	**0.166**	**0.114**	0.056	-0.110	**0.494**	**0.406**	**0.504**	0.010
	(0.046)	(0.044)	(0.047)	(0.065)	(0.035)	(0.034)	(0.036)	(0.050)
Size- and Growth Neutral	**0.386**	**0.329**	**0.222**	**-0.164**	**0.360**	**0.337**	**0.451**	**0.091**
	(0.038)	(0.038)	(0.043)	(0.057)	(0.029)	(0.029)	(0.032)	(0.043)
FC(High KZ-Low KZ)	1.230							
	(1.730)							

Table 11: Continued

Panel B: Discount Rate and Cash Flow Betas of 5-year Returns

	$\beta_{i,DRM}$				$\beta_{i,CFM}$			
	Low KZ	Middle KZ	High KZ	diff	Low KZ	Middle KZ	High KZ	diff
Small	**-0.120**	**-0.155**	**-0.205**	-0.085	**0.290**	**0.350**	**0.407**	**0.118**
	(0.049)	(0.052)	(0.054)	(0.073)	(0.036)	(0.038)	(0.040)	(0.054)
Median	-0.020	**-0.150**	**-0.296**	**-0.277**	**0.305**	**0.223**	**0.292**	-0.014
	(0.038)	(0.038)	(0.043)	(0.057)	(0.028)	(0.028)	(0.032)	(0.042)
Big	**0.245**	**0.155**	0.032	**-0.214**	**-0.047**	0.013	**0.124**	**0.170**
	(0.028)	(0.029)	(0.032)	(0.042)	(0.021)	(0.021)	(0.024)	(0.031)
Low	**0.234**	**0.142**	0.003	**-0.232**	**0.132**	**0.207**	**0.291**	**0.159**
	(0.032)	(0.033)	(0.052)	(0.061)	(0.024)	(0.025)	(0.039)	(0.045)
Neutral	-0.006	-0.022	**-0.240**	**-0.234**	**0.148**	**0.135**	**0.256**	**0.109**
	(0.035)	(0.035)	(0.047)	(0.058)	(0.026)	(0.026)	(0.034)	(0.043)
High	**-0.132**	**-0.132**	**-0.239**	-0.106	**0.243**	**0.167**	**0.253**	0.010
	(0.044)	(0.043)	(0.043)	(0.061)	(0.032)	(0.032)	(0.031)	(0.045)
Size- and Growth Neutral	**0.116**	0.045	**-0.087**	**-0.203**	**0.230**	**0.221**	**0.314**	**0.084**
	(0.040)	(0.040)	(0.044)	(0.059)	(0.029)	(0.029)	(0.032)	(0.044)
FC(High KZ-Low KZ)	2.520							
	(2.530)							

Panel A of table 5 reports discount rate and cash flow betas of 2-year returns. For every month in year t, portfolios are constructed to be held until year t+2 using the accounting information available by t. Then I regress holding period portfolio return on the corresponding market news, where the market news is the aggregation of my monthly VAR estimates over 2 years. Panel A gives estimates of betas for size-neutral, growth-neutral and size- and growth- neutral portfolios. The last row of the panel gives an estimate of financial constraint premium FC (High KZ-Low KZ) for size- and growth- neutral portolio, in percent. Panel B extends the exercise to 5 years' investment horizon. All standard errors are in parenthesis. The bold font indicates significance level of 5%.

Table 12: Preformation Monthly Return of Switchers and Stayers

Panel A: Summary Statistics of Stayers' and Switchers' Returns

Year	Standard Deviation			Correlation with Switchers	
	FC_{SW}	FC_{ST}	FC	FC_{ST}	FC
t-5	4.277	4.638	2.185	0.149	0.009
t-4	5.262	4.609	2.172	0.219	0.054
t-3	4.747	4.359	2.181	0.222	0.088
t-2	5.476	4.537	2.184	0.270	0.213
t-1	5.314	4.365	2.186	0.319	0.171
t	4.505	4.208	2.193	0.378	0.213

Table 12: Continued

Panel B: Switchers and Stayers Return Regressions

	Stayers		Switchers		Switchers	
	Coefficient on FC	R^2	Coefficient on FC	R^2	Coefficient on FC_{ST}	R^2
t-5	**0.764**	0.129	0.018	0.000	**0.137**	0.022
	(0.092)		(0.091)		(0.042)	
t-4	**0.700**	0.109	0.131	0.003	**0.250**	0.048
	(0.091)		(0.109)		(0.050)	
t-3	**0.773**	0.150	0.192	0.008	**0.242**	0.049
	(0.083)		(0.098)		(0.048)	
t-2	**0.780**	0.141	**0.534**	0.045	**0.326**	0.073
	(0.087)		(0.111)		(0.052)	
t-1	**0.805**	0.162	**0.415**	0.029	**0.388**	0.102
	(0.083)		(0.108)		(0.052)	
t	**0.753**	0.154	**0.438**	0.045	**0.405**	0.143
	(0.081)		(0.092)		(0.045)	
Diff(-5 to 0)	0.011		**-0.420**		**-0.268**	
	(0.122)		(0.129)		(0.062)	

Panel A presents summary statistics of switcher and stayer portfolios. The switcher is defined as those stocks who was in different KZ group by year t as in year t-5, whereas the stayer is those of which are in the same KZ group in year t and year t-5. Both return on the switchers and stayers are obtained by taking long position on those constrained stocks and short position on those unconstrained stocks. FC is the size and book-to-market stratified portfolio following the definition in table 4. Panel B gives univariate regression results on stayers and switchers. The sample period is from 1964:7 to 2008:6. All standard errors are in parenthesis. The bold font indicates significance level of 5%.

Table 13: Preformation Cash Flow News of Switchers

	Correlation with Switchers				Regression on Switchers			
	roest	roekz	cfst	cfkz	roest	roekz	cfst	cfkz
t-5	0.015	-0.294	0.183	-0.319	0.078	-0.480	0.190	-0.485
					(0.253)	(0.273)	(0.177)	(0.251)
t-4	-0.058	-0.093	0.107	0.367	0.107	-0.108	0.200	**0.233**
					(0.263)	(0.120)	(0.313)	(0.100)
t-3	0.061	0.094	-0.332	0.242	0.090	0.020	**-0.585**	0.190
					(0.327)	(0.139)	(0.281)	(0.129)
t-2	0.129	0.280	0.025	0.271	0.167	0.212	0.043	0.234
					(0.233)	(0.123)	(0.297)	(0.141)
t-1	-0.038	-0.035	-0.313	-0.469	0.383	-0.066	-1.749	**-1.018**
					(0.963)	(0.393)	(0.896)	(0.324)
t	0.358	0.171	0.499	0.318	**0.943**	0.212	**0.767**	**0.236**
					(0.403)	(0.189)	(0.228)	(0.121)
Diff	-0.343	-0.465	-0.316	-0.637	-0.865	**-0.693**	**-0.577**	**-0.721**
					(0.475)	(0.332)	(0.289)	(0.279)

This table reports preformation cash flow news comovement of switchers. The first 4 columns gives correlation of switchers' cash flow news with stayers' and FC's. roest denotes the contemporaneous accounting return on equity of stayers in year t, where ROE is computed based on equation in the main article. roekz is the return on equity of FC in year t. cfst measures the cash flow news of stayers at 5-year horizon and cfkz measures that of FC at 5-year horizon. The second 4 column reports univariate regression results of various portfolios cash flow on the switchers' cash flow news, measured at one year and 5 years respectively to be consistent with independent variables. All these cash flow measures are based on accounting ratios and at yearly frequency. The sample period is from 1964 to 2008. All standard errors are in parenthesis. The bold font indicates significance level of 5%.

Table 14: Monthly 2-beta Regression of Switchers and Stayers

	Stayers		Switchers	
	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$
t-5	**0.240**	**0.577**	-0.045	-0.111
	(0.068)	(0.137)	(0.066)	(0.131)
t-4	**0.250**	**0.686**	0.010	0.140
	(0.067)	(0.134)	(0.080)	(0.159)
t-3	**0.300**	**0.621**	-0.031	0.131
	(0.063)	(0.125)	(0.072)	(0.142)
t-2	**0.282**	**0.755**	**0.232**	**0.682**
	(0.066)	(0.129)	(0.081)	(0.160)
t-1	**0.155**	**0.656**	0.118	**0.367**
	(0.064)	(0.127)	(0.079)	(0.157)
t	**0.200**	**0.595**	0.061	0.253
	(0.062)	(0.122)	(0.068)	(0.135)
Diff	0.040	-0.018	-0.107	**-0.364**
	(0.092)	(0.183)	(0.095)	(0.189)

This table exhibits the 2-beta regression on swichers' and stayers' monthly return, where market news is based on VAR estimates in table 1. One lag of the market news is included also to alleviate the nonsynchronization issues pointed by Campbell and Vuolteenaho (2004). Hence the cash flow beta is $\frac{cov(r_{i,t},\widehat{N_{CF,t}})+cov(r_{i,t},\widehat{N_{CF,t-1}})}{Var(r_m)}$ and the discount rate beta is $\frac{cov(r_{i,t},-\widehat{N_{DR,t}})+cov(r_{i,t},-\widehat{N_{DR,t-1}})}{Var(r_m)}$. The sample period is from 1964:7 to 2008:6. All standard errors are in parenthesis. The bold font indicates significance level of 5%.

Table 15: Cash Flow and Discount Rate Betas of WW Index Sorted Portfolios

Panel A: Monthly Regression on Size and WW sorted portfolios

	Small Cap		Median Cap		Big Cap		Diff (S-B)	
	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$
Low WW (Unconstrained)	1.137	0.665	1.167	0.605	1.029	0.457	0.133	**0.405**
	(0.081)	(0.117)	(0.048)	(0.070)	(0.026)	(0.038)	(0.082)	(0.127)
Middle WW	1.167	0.844	1.284	0.661	1.457	0.493	0.140	**0.321**
	(0.060)	(0.087)	(0.047)	(0.068)	(0.053)	(0.077)	(0.075)	(0.117)
High WW (Constrained)	1.374	0.885	1.700	0.712	1.889	0.605	**0.183**	**0.371**
	(0.071)	(0.102)	(0.068)	(0.099)	(0.129)	(0.187)	(0.092)	(0.139)
Diff(C-U)	**0.237**	0.219	**0.533**	0.107	**0.860**	0.147		
	(0.108)	(0.156)	(0.084)	(0.121)	(0.132)	(0.191)		

Panel B: Monthly Regression on Book-to-Market and WW sorted portfolios

	Low Btm		Neutral Btm		High Btm		Diff (L-H)	
	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$	$\beta_{i,DRM}$	$\beta_{i,CFM}$
Low WW (Unconstrained)	1.125	0.394	1.027	0.522	1.024	0.551	**0.256**	-0.136
	(0.026)	(0.038)	(0.032)	(0.046)	(0.041)	(0.059)	(0.069)	(0.100)
Middle WW	1.484	0.564	1.323	0.710	1.124	0.685	**0.294**	-0.022
	(0.053)	(0.077)	(0.048)	(0.069)	(0.050)	(0.072)	(0.062)	(0.090)
High WW (Constrained)	1.711	0.815	1.445	0.824	1.263	0.867	**0.429**	-0.021
	(0.075)	(0.109)	(0.070)	(0.101)	(0.066)	(0.096)	(0.088)	(0.127)
Diff(C-U)	**0.586**	**0.421**	**0.419**	**0.302**	**0.239**	**0.316**		
	(0.080)	(0.115)	(0.077)	(0.111)	(0.078)	(0.112)		

Table 15: Continued

Panel C: Monthly Regression on Size- and Growth- Neutralized Portfolios			
	$\beta_{i,DRM}$	$\beta_{i,CFM}$	R_i in %
Low WW (Unconstrained)	**1.085**	**0.532**	**1.060**
	(0.033)	(0.048)	(0.220)
Middle WW	**1.307**	**0.659**	**1.190**
	(0.046)	(0.066)	(0.269)
High WW (Constrained)	**1.567**	**0.782**	**1.450**
	(0.067)	(0.097)	(0.335)
Diff (C-U)	**0.482**	**0.250**	0.390
	(0.075)	(0.108)	(0.401)

This table shows the cross-sectional cash flow and discount betas of WW, size and growth sorted portfolios. It has the same setting as table 3. All standard errors are in parenthesis. The bold font indicates significance level of 5%.

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