

Cash Flow and Discount Rate Risk in the Investment Effect:

A Downside Risk Approach

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Abstract

We examine whether sensitivities to cash flow (CF) and discount rate (DR) risk in down markets provide an explanation for the investment effect, where low-investment stocks earn higher expected returns than high-investment stocks. We show how productivity and financing constraints asymmetrically impact the systematic risk of low-investment and high-investment firms, conditional on market state. Our evidence is consistent with both productivity constraints and financing constraints as explanations for the investment effect but, contrary to expectations, more when prices are rising than when falling.

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1. Introduction

The role of firm-specific capital investment in explaining the cross section of stock returns has been a fruitful area of research in the last few decades. The investment effect refers to the empirical finding that companies that invest more (often referred to as the investment growth effect; see Titman, Wei, and Xie, 2004; Xing, 2008, Prombutr, Phengpis, and Zhang, 2012) or grow their total assets more (often referred to as the asset growth effect; see Cooper, Gulen, and Schill, 2008; Cooper and Priestley, 2011; Lam and Wei, 2011; Watanabe et al., 2013; Huang and Wang, 2014) earn lower subsequent risk-adjusted returns. The investment effect has been found to be an important determinant of firm-level stock returns (e.g., Carlson, Fisher, and Giammarino, 2004; Anderson and Garcia-Feijoo, 2006; Liu, Whited, and Zhang, 2009; Chen, Novy-Marx, and Zhang, 2011), and aggregate market returns (e.g., Cochrane, 1991 and 1996; Lamont, 2000; Lettau and Ludvigson, 2001 and 2002; Li, Vassalou, and Xing, 2006).

The literature on the investment effect suggests that the determinants of the investment effect come from both the left-hand side (investment policy) and the right-hand side (financing policy) of the balance sheet. More specifically, there are two channels that can be used to explain the negative association between current investment and future stock returns – a permanent, fundamental cash flow (CF) channel (driving the investment policy) and a transitory, financial discount rate (DR) channel (driving the financing policy). The CF channel works through frictions in capital adjustment, and it implies that after controlling for discount rates, the higher the expected future marginal productivity of capital, the higher will be current investment. Under diminishing returns to scale, this implies a lower marginal productivity of capital, and thus lower expected stock returns as firms exploit additional investment opportunities (among others, Li, Livdan, and Zhang, 2009). The DR channel works through the costly external financing frictions

and it suggests that after controlling for expected cash flows, the lower the discount rate, the higher will be current investment, and the lower will be future stock returns (Cochrane, 1996; Lamont, 2000; Li, Vassalou, and Xing, 2006; Liu, Whited, and Zhang, 2009).

In this paper, we investigate whether the CF channel (which work through productivity constraints) and the DR channel (which work through financing constraints) are felt asymmetrically by low-investment and high-investment firms during market downturns. To test this idea, we formulate two hypotheses and investigate them empirically. The CF channel gives rise to a ‘productivity constraints hypothesis’ and the DR channel motivates a ‘financing constraints hypothesis.’ The productivity constraints hypothesis states that the CF risk exposures of low-investment firms differ from those of high-investment firms during market downturns. The asymmetric sensitivities of firms’ stock returns to CF news about investment or asset growth rates is based on the notion that although recessions are periods typically associated with disinvestment for all firms, low-investment firms tend to be riskier when market sentiment is negative due to the fact that they have less flexibility in adjusting their capital stock than high-investment firms (Zhang, 2005; Cooper, 2006; Lin, 2012). Our second hypothesis argues that financing frictions are felt asymmetrically by low-investment and high-investment firms during down markets. An asymmetric DR effect implies that although market downturns are typically associated with an increase in the cost of external finance (Bernanke and Gertler, 1989), the exceptionally-adverse financing constraints in bad times are likely to impact high-investment firms more than low-investment firms (Smith and Watts, 1992; Duchin, Ozbas, and Sensoy, 2010; Arnold, Wagner, and Westermann, 2013; Nishihara and Shibata, 2013).

The motivation for our study derives from the results of a growing number of papers which model the role that downside risk plays on firms’ productivity constraints (i.e., capital

adjustment costs driving CFs) and financing constraints (i.e., costly external finance decisions motivated by DRs) (Bernanke and Gertler, 1989; Rousseau and Kim, 2008; Duchin, Ozbas, and Sensoy, 2010; Campello, Graham, and Harvey, 2010; Nishihara and Shibata, 2013; Shibata and Nishihara, 2015). However, these frictions are felt asymmetrically by low-investment and high-investment firms during market downturns (Smith and Watts, 1992; Zhang, 2005; Cooper, 2006; Cooper, Gulen, and Schill, 2008; Duchin, Ozbas, and Sensoy, 2010; Lin, 2012; Arnold, Wagner, and Westermann, 2013; Ding, Guariglia, and Knight, 2013; Nishihara and Shibata, 2013).

We employ and expand beta decomposition methods of Campbell (1991), Campbell and Vuolteenaho (2004), and Botshekan, Kraeussl, and Lucas (2012) in order to test the productivity and financing hypotheses as potential explanations for the investment effect. The beta decomposition procedures suggested by Campbell (1991) show that stock returns are driven by cash flow and discount rate news. We take a step forward in bringing the beta decomposition approach to the real investment setting. Therefore, we employ a multi-factor beta decomposition model in order to parse the effects of downside risk on the firm's investment policy (CF risk) and financing decisions (DR risk). We define CF and DR investment betas by conditioning a firm's stock return covariation with CF news and DR news, respectively, about investment growth rates (rather than stock returns). Following Ang, Chen, and Xing (2006), and Botshekan, Kraeussl, and Lucas (2012), we define downside betas by conditioning a stock return's covariation with the market only when the market return is negative.

The article contributes to the literature in two ways. First, we provide a theoretical and empirical exploration of the investment effect by examining the ability of CF and DR news about investment and asset growth rates to explain variation in stock returns. Although many papers have devoted much effort to understanding the investment effect (e.g., Cochrane, 1996; Lamont,

2000; Li, Vassalou, and Xing, 2006; Xing, 2008; Li, Livdan, and Zhang, 2009; Liu, Whited, and Zhang, 2009), little is known about the quantitative importance of CF and DR news in explaining this effect. Second, to the best of our knowledge, our paper is the first one that empirically tests the impact of CF and DR news about investment rates conditional on the state of the market. The closest in this respect is the recent work by Botshekan, Kraeussl, and Lucas (2012). However, our paper is different in the sense that we focus on news about investment rates, while Botshekan, Kraeussl, and Lucas (2012) analyze news about stock returns.

Our empirical analysis validates our theoretical model and provides several new results about the investment effect. Our central findings can be summarized as follows. We show that low-investment and high-investment firms respond asymmetrically to the CF and DR components of investment growth rates across market conditions, but firm size is an important determinant in explaining these associations. More specifically, our results provide support for the productivity constraints hypothesis, but only for small firms in the context of our model. We find that small firms with less investment and asset growth are more sensitive to aggregate CF news than small firms with high investment and asset growth in downside conditions, while large firms display the opposite pattern. Furthermore, our results are consistent with the role of financing constraints as a partial explanation for the investment effect, but only for large firms. We show that large firms display increasing sensitivities to DR news as investment levels increase in downside conditions. We find also that firm-level information allows for much more meaningful measures of CF and DR news than does market-wide information, especially when one is concerned about variation across firms with different levels of capital investment.

Our story proceeds as follows. Section (2) motivates our investigation by expanding existing models of CF and DR news, allowing us to specify the testable hypotheses concerning

the role of market conditions in explaining the investment effect. Section (3) illustrates the empirical procedures used to test our model. Section (4) describes the data and variable construction. Section (5) presents the results of our analysis, and section (6) offers conclusions.

2. Theoretical Framework

2.1 Modeling Investment Returns

We present a well-known existent production-based model which motivates our empirical approach. The model belongs to a growing literature that explores the implications of production and investment on the cross section of returns using a production-based asset pricing model. Examples of this line of research include Cochrane (1991 and 1996); Lamont (2000); Gomes, Kogan, and Zhang (2003); Gomes, Yaron, and Zhang (2006); Li, Vassalou, and Xing (2006); Li, Livdan, and Zhang (2009); Liu, Whited, and Zhang (2009); Li and Zhang (2010); and Jermann (2010 and 2013). Our goal in this subsection is to use the existing literature to derive an expression for investment returns in the presence of productivity and financial frictions in a production-based asset pricing framework.

Consider a firm i that makes financing and investment decisions to maximize the value of existing shareholders. For the financing decisions, the firm uses equity and debt financing to choose the optimal amount of capital at the beginning of the next period $K_{i,t+1}$. When the sum of current level of investment $I_{i,t}$ and adjustment costs exceeds internal funds $\pi(K_{i,t})$ at the beginning of period t , the firm can finance investment through selling new equity $N_{i,t}$ and issuing new debt $B_{i,t+1}$ which must be repaid at the end of period $t + 1$. Let $R_{i,t}^B$ refers to the interest rate plus principal repayment per dollar of new debt raised $B_{i,t+1}$, and we assume that $R_{i,t}^B$ is independent of firm characteristics. The dividend payout $D_{i,t}$ to the existing shareholders

therefore equals the internal funds $\pi(K_{i,t})$ plus the new external funds $(N_{i,t} + B_{i,t+1})$ minus the cost of investment $\phi(I_{i,t}, K_{i,t})^1$ and the net cost of debt $R_{i,t}^B B_{i,t}$.

For the investment decisions, the firm uses capital stock $K_{i,t}$ and other costless inputs to produce homogeneous output. The firm's production function is the standard Cobb-Douglas production function which is given by $Y_{i,t} = (K_{i,t})^\alpha (x_t)^{1-\alpha}$ where α is the capital share that reflects the elasticity of output with respect to capital, and x_t is the aggregate productivity. The production function exhibits diminishing returns to scale ($0 < \alpha < 1$) which means that more investment leads to a lower marginal product of capital. Given such a setup, the value maximization problem of the firm's cum-dividend market value of equity, denoted as $V_{i,t}$, therefore can be summarized as

$$V_{i,t} \equiv \max E_t [M_{t+1} D_{i,t+1}] \quad (1)$$

$$\text{Subject to: Capital Accumulation Constraint: } K_{i,t+1} = I_{i,t} + (1 - \delta_{i,t})K_{i,t} \quad (2)$$

$$\text{Dividend Constraint: } D_{i,t} > \overline{D_{i,t}} \quad (3)$$

Equation (1) is the firm maximization problem where M_{t+1} is the stochastic discount factor from t to $t + 1$. Equation (2) is the standard capital accumulation production constraint facing the firm where the level of capital stock in the end of period $K_{i,t+1}$ depends on three factors: the current capital stock $K_{i,t}$, the current investment level $I_{i,t}$ and the depreciation rate of existing capital $\delta_{i,t}$. Equation (3) is the dividend payment constraint that implies that the firm's dividend must be greater than the minimum dividend $(\overline{D_{i,t}})$.

¹ The firm's costs of investment $\phi(I_{i,t}, K_{i,t})$ equals the invested capital $I_{i,t}$ plus the adjustment cost, as follows

$$\phi(I_{i,t}, K_{i,t}) = I_{i,t} + \left(\frac{a}{2} \left(\frac{I_{i,t}}{K_{i,t}} \right)^2 K_{i,t} \right)$$

The second term is the capital adjustment cost function. Following the literature (e.g., Li, Livdan, and Zhang, 2009; and Liu, Whited, and Zhang, 2009), we assume that the adjustment cost function is quadratic in capital growth where $a > 0$ is a constant parameter that captures the curvature of the adjustment cost.

Let $q_{i,t}$ (or what is called marginal q) be the Lagrangian multiplier associated with the capital accumulation constraint. The optimality condition with respect to $K_{i,t}$ equals

$$q_{i,t} = E_t \left[M_{t+1} \left(\frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} - \frac{\partial \phi(I_{i,t+1}, K_{i,t+1})}{\partial K_{i,t+1}} + (1 - \delta_{i,t+1})q_{i,t+1} \right) \right] \quad (4)$$

Equation (4) is the investment Euler equation which discounts the expected marginal profits of investment dated $t + 1$ (the term in bracket) back to t , using the stochastic discount factor M_{t+1} . The marginal product of capital is given by $\partial \pi(K_{i,t+1})/\partial K_{i,t+1}$, the marginal reduction in adjustment costs generated by an extra unit of capital is given by $\partial \phi(I_{i,t+1}, K_{i,t+1})/\partial K_{i,t+1}$, and the marginal liquidation value of capital net of depreciation is given by $(1 - \delta_{i,t+1})q_{i,t+1}$. Discounting these marginal profits of investment at time $t+1$ back to time t using the stochastic discount factor M_{t+1} yields $q_{i,t}$. Dividing both sides of equation (4) by $q_{i,t}$, we obtain

$$E_t \left[M_{t+1} \left(\frac{\frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} - \frac{\partial \phi(I_{i,t+1}, K_{i,t+1})}{\partial K_{i,t+1}}}{q_{i,t}} + \frac{(1 - \delta_{i,t+1})q_{i,t+1}}{q_{i,t}} \right) \right] = E_t \left[M_{t+1} \left(\tilde{R}_{i,t}^I \right) \right] = 1 \quad (5)$$

We can define investment returns in the absence of financing frictions $\tilde{R}_{i,t}^I$ as the term in the bracket in equation (5), as the standard investment returns derived from the standard production based models (e.g., Cochrane, 1991 and 1996; Li, Vassalou, and Xing, 2006; Liu, Whited, and Zhang, 2009). The investment returns measures the stochastic rate of return that results from investing a little more today and then investing a little less tomorrow. Following Gomes, Yaron and Zhang (2006), we incorporate financing frictions in the model by letting μ_t be the Lagrange multiplier associated with the dividend constraint defined by equation (3). The investment return in the presence of financing frictions, denoted as R_t^I , thus can be stated as

$$R_{i,t}^I \equiv \left(\frac{1 + \mu_{i,t+1}}{1 + \mu_{i,t}} \right) (\tilde{R}_{i,t}^I) \equiv \left(\frac{1 + \mu_{i,t+1}}{1 + \mu_{i,t}} \right) \left(\frac{\frac{\partial \pi(K_{i,t+1})}{\partial K_{i,t+1}} - \frac{\partial \phi(I_{i,t+1}, K_{i,t+1})}{\partial K_{i,t+1}} + (1 - \delta_{i,t+1})q_{i,t+1}}{q_{i,t}} \right) \quad (6)$$

2.2 CF and DR Channels of Investment Returns

Both equations (4) and (6) predict that there are two major channels – fundamental and financing – which affect both investment levels and returns, respectively.² Equation (4) measures the shadow price of capital as the present value of the marginal products of depreciating capital and breaks the determinants of the cyclical variability of investment down into two components – fundamental factors (variations in the marginal profits of investment) and financing factors (variations in the discount rate) (Abel and Blanchard, 1986; Gilchrist and Himmelberg, 1995; Love and Zicchino, 2006). Similarly, equation (6) measures investment returns in the presence of both financing constraints (first term) and productivity constraints (second term) (Li, Vassalou, and Xing, 2006; Liu, Whited, and Zhang, 2009; Li, Livdan, and Zhang 2009). The impact of financing frictions on investment returns is captured by the term $(1 + \mu_{i,t+1})/(1 + \mu_{i,t})$ which refers to the shadow price of external funds. In the absence of financing constraints (i.e., $\mu_{i,t+1} = \mu_{i,t}$), investment return is affected only by productivity constraints. We call the two forces cash flow (CF) and discount rate (DR) channels which give rise to two competing forces that influence the response of stock returns to investment returns.

The CF channel measures the elasticity of investment return with respect to the future marginal profits of investment. The CF channel is driven only by fundamentals (i.e., revenue, investment, and capital) and it works only through frictions in capital adjustment. According to the standard Q-theory as proposed by Tobin (1969), investment is frictionless which implies that

² Taken together, both equations (4) and (6) are analogous to stock price and return equations, respectively, as in the work of Liu, Whited, and Zhang (2009).

the firm can instantaneously and costlessly adjust its capital stock. The absence of productivity frictions thus means that the firm is fully responsive to any changes in the marginal productivity of capital (i.e., the firm can instantaneously and costlessly adjust its capital stock). When investing, however, the firm incurs adjustment costs which reflect the firm's foregone operating profit (i.e., opportunity cost) it would have made had it not invested, since the firm has to reduce sales to increase investment (Eisner and Strotz, 1963; Lucas, 1967; Cochrane, 1991; Liu, Whited, and Zhang, 2009). The capital adjustment frictions give rise to the CF channel which prevents firms from adjusting their capital stock instantaneously, leading to a lagged response to various exogenous economic shocks. The CF channel therefore predicts that, after controlling for discount rates, the higher the expected future marginal productivity of capital, the higher will be current investment (Li, Livdan, and Zhang, 2009).

The DR channel measures the elasticity of investment return with respect to the stochastic discount rate. The DR channel is a function of financing factors (i.e., discount rates) and it works only through costly external financing frictions. In the absence of financing constraints (i.e., $\mu_{i,t+1} = \mu_{i,t}$ in equation (6)), internal and external funds are perfect substitutes and the firm's investment will be fully responsive to changes in discount rates. However, there are several factors that make external finance more costly than internal finance, such as asymmetric information, agency costs, market timing issues, and flotation costs (Fazzari, Hubbard, and Peterson, 1988; Love and Zicchino, 2006; Ascioglu, Hegde, and McDermott, 2008; Guariglia, 2008; Li and Zhang, 2010). These market imperfections give rise to the DR channel which makes the firm's investment less elastic to changes in discount rates. This leads to a lagged response to various exogenous economic shocks. The DR channel thus predicts that after controlling for expected cash flows, the lower the discount rate, the higher will be the

current investment, and the lower will be the future returns on that investment (Cochrane, 1996; Lamont, 2000; Li, Vassalou, and Xing, 2006; Liu, Whited, and Zhang, 2009; Li and Zhang, 2010).

2.3 Testable Hypotheses: Asymmetric CF and DR channels

Our goal is to investigate whether CF risks (which work through productivity frictions) and DR risks (which work through financing frictions) are felt asymmetrically by low- and high-investment firms during market downturns. To test this conjecture, we develop two hypotheses to investigate a downside risk-based explanation for the investment effect based on the asymmetric exposure of high- and low-investment firms to productivity and financing frictions.

Our first hypothesis is developed from the literature on asymmetric beta dispersion that result from the asymmetric capital adjustment costs (or irreversible investment) (Zhang, 2005; Cooper, 2006; Ozdagli, 2012; Lin, 2012). Irreversible investment is considered a special case of cost reversibility and it implies that an average firm faces higher costs in downscaling during recessions than in expanding their capacity during booms. Our first hypothesis implies that the CF channel works asymmetrically for low and high investment firms. The asymmetric CF channel predicts that although recessions are periods typically associated with disinvestment for all firms, low-investment firms tend to have less flexibility in adjusting their capital stock (i.e., downscaling) in bad times than high-investment firms.

There are two reasons for such inflexibility of low-investment firms – one is related to their investment-sizing policy and the other one is related to the timing policy. First, low-investment firms have less flexibility in adjusting capital stock in bad times, since they are likely to be burdened with excessive unproductive capital. As supportive evidence, a growing number of papers find that low-investment firms disinvest more than high-investment firms during

periods of economic downturns (e.g., Zhang, 2005; Cooper, 2006; Lin, 2012). Second, the standard framework for the investment timing policy is the real option models³ (e.g., Berk, Green, and Naik, 1999; Gomes, Kogan, and Zhang, 2003; Carlson, Fisher, and Giammarino, 2004; Andrikopoulos, 2009), which show that there exists a value of waiting to invest. During recessions, the value of the option-to-wait is higher due to the potential of an improvement in the economy, and consequently, the time-to-exercise growth option lengthens. As high-investment firms derive most of their value from growth options, we should expect high-investment firms to be more flexible during recessions since they have the choice to postpone implementation of their options until the economy recovers. Conversely, low-investment firms do not have such an option because they derive most of their value from assets-in-place. Therefore, low-investment firms tend to be less profitable when macroeconomic conditions are unfavorable (Morellec and Schürhoff, 2011; Ai and Kiku, 2013; Arnold, Wagner, and Westermann, 2013). This argument leads to our first hypothesis:

H1. Productivity Constraints Hypothesis: *The stock returns of low-investment firms are more sensitive to downside CF news about investment returns relative to high-investment firms.*

The second hypothesis builds on the literature on costly external finance in the presence of downside risk (e.g., Bernanke and Gertler, 1989; Gomes, Yaron, and Zhang, 2006; Chen, 2010; Frank and Goyal, 2009; Campello, Graham, and Harvey, 2010; Kahle and Stulz, 2013; Shibata and Nishihara, 2015). This literature predicts that market downturns are accompanied with a contraction in the supply of external financing, an increase in the cost of external funds,

³ The real option models portray firm value as the sum of the value of existing assets (measured by summing the present value of future cash flows from all ongoing projects) and the value of the growth options (measured by the present value of all future positive NPV projects). In these models, the cash flow (CF) perspective holds project revenue risks constant and focuses on the numerator of the present value formula through decomposing the cash flow among revenues from the existing assets and growth options (Berk, Green, and Naik, 1999; Gomes, Kogan, and Zhang, 2003). In contrast, the discount rate (DR) perspective holds expected cash flows constant and focuses on the denominator of the valuation equation by examining the cross-sectional dispersion in new project betas (Carlson, Fisher, and Giammarino, 2004).

and an increase in default risk and costs. Our second hypothesis implies that the DR channel works asymmetrically for low and high investment firms. The asymmetric DR channel works through asymmetric financing constraints which reflect the asymmetry in costly external financing between low and high-investment firms during market downturns.

There are several reasons to associate financing inflexibility with high-investment firms during downturns relative to low-investment firms. First, the exceptionally-adverse financing constraints are likely to have more impact on high-investment firms with less collateral for external financing than low-investment firms. Second, firms with high proportions of growth options (high-investment firms) are associated with higher costs of debt due to the underinvestment problem (Smith and Watts, 1992), higher default probabilities, higher default costs, and larger credit spreads during downturns (Arnold, Wagner, and Westermann, 2013). Third, although recessions are typically associated with an increase in the importance of internal financing due to increasing the cost of debt, the impact of internal resources (cash reserves) on post-crisis investment is stronger for financially constrained firms (Rousseau and Kim, 2008; Duchin, Ozbas, and Sensoy, 2010) and for growth firms with low internal funds compared to mature firms with high internal funds (Nishihara and Shibata, 2013). Based on this discussion, we have the following hypothesis:

H2. Financing Constraints Hypothesis: *The stock returns of high-investment firms are more sensitive to downside DR news about investment returns relative to low-investment firms.*

The story of our paper can thus be summarized as follows. In normal times, investment returns may be driven by two channels – the CF channel, working through productivity frictions, and the DR channel, working through financing frictions. Both channels work symmetrically for low-investment firms and high-investment firms during normal times. When an investment

shock hit the market, however, these two channels start to work differently for low-investment firms and high-investment firms depending on whether the aggregate investment shock is driven by cash flow or discount rate shocks.⁴ If the aggregate investment shock is due to a decrease in rational expectations of future profits of future investment (i.e., change in the CF channel), the asymmetric CF channel (hypothesis 1) predicts that low-investment firms tend to be less flexible in adjusting their capital and thus tend to be riskier than high-investment firms.⁵ Conversely, if the aggregate investment shock is driven by a large increase in the discount rates applied to profits of future investment (i.e., change in the DR channel), the asymmetric DR channel (hypothesis 2) predicts that high-investment firms tend to be less flexible in obtaining new capital in bad times and thus tend to be riskier than low-investment firms.⁶

3. Empirical Methodology

The beta decomposition procedures introduced by Campbell (1991) and Campbell and Vuolteenaho (2004) suggest that stock returns are driven by two channels – a permanent, fundamental cash flow (CF) channel and a transitory, financing discount rate (DR) channel. We take a step forward in bringing this beta decomposition approach to the real investment setting. More specifically, we use Campbell and Vuolteenaho (2004) return decomposition approach to

⁴ Campbell, Giglio, and Polk (2013) identify two major causes of market downturns – cash flow and discount rate shocks. For example, they find that the 2000–2002 downturn was due to discount rate shocks, while the 1937–1938 associated with the Great Depression and 2007–2009 downturn was due to cash flow shocks.

⁵ In production economies, the less flexibility a firm has, the riskier it is. The asymmetry in capital adjustment thus can be translated into asymmetry in betas between low and high-investment firms during recessions. Consistent with this, Cooper and Priestley (2011) find that low-investment firms have substantially higher loadings with respect to the Chen, Roll, and Ross (1986) factors than high-investment firms. In addition, Ai and Kiku (2013) and Ai, Croce, and Li (2013) document that the pro-cyclical dynamics of the price of capital goods (the physical resources required for exercising options) makes growth options less vulnerable to aggregate risks compared to assets-in-place when macroeconomic conditions are unfavorable.

⁶ In support of such views, Arnold, Wagner, and Westermann (2013) show that firms with valuable growth options are more sensitive to macroeconomic regime changes than firms that consist of assets-in-place only.

empirically decompose aggregate investment returns into two competing forces – a fundamental cash flow (CF) investment channel and a financing discount rate (DR) investment channel.

Our intuition for applying the Campbell and Vuolteenaho (2004) approach to decompose investment returns into CF and DR news has three aspects. The first is based on the analogy between stock returns and investment returns, as in Cochrane (1991). Equations (4) and (5) are analogous to stock price and return equations, respectively, as in the work of Liu, Whited, and Zhang (2009). In particular, equation (4) is analogous to the stock price as it measures the shadow price of capital as the present value of the marginal products of depreciating capital discounted at the stochastic discount factor M_{t+1} . Equation (5) is analogous to stock returns, as it measures investment returns as the sum of two ratios where the first ratio is proportional to the marginal productivity of capital $((\partial\pi(K_{i,t+1})/\partial K_{i,t+1})/q_{i,t})$ (analogous to the stock dividend yield), and the second ratio is a function of investment growth $((1 - \delta_{i,t+1})q_{i,t+1}/q_{i,t})$ (analogous to the capital yield component of stock return).

Second, Campbell and Shiller (1988) develop a log-linear present value relation between stock prices and dividends, based on an accounting framework: high prices must be followed by high future dividends, low future returns, or some combination of both. Analogous to their intuition, the present value relation between the future marginal profit of investment and capital prices can also provide an accounting framework. In particular, equation (4) says that high capital prices, $q_{i,t}$, must be followed by high expected future marginal profits of investment, or low future returns, M_{t+1} , or some combination of both (Abel and Blanchard, 1986; Gilchrist and Himmelberg, 1995; Love and Zicchino, 2006).

Third, one of the appealing intuitions in the Campbell and Vuolteenaho (2004) paper is the presence of investors with different horizons, which may require different premia for

different types of risks. Similarly, we argue that low-investment and high-investment firms have different characteristics, which give rise to asymmetric risk exposures during market downturns (Smith and Watts, 1992; Zhang, 2005; Cooper, 2006; Cooper, Gulen, and Schill, 2008; Duchin, Ozbas, and Sensoy, 2010; Lin, 2012; Arnold, Wagner, and Westermann, 2013; Ding, Guariglia, and Knight, 2013; Nishihara and Shibata, 2013).

3.1 Empirical Estimation of CF and DR Betas

In order to empirically model our hypotheses, we estimate vector auto-regressions (VARs) for aggregate investment returns in the manner of Campbell, Polk, and Vuolteenaho (2010). In particular, we use the following first-order vector autoregressive (VAR) model to forecast the aggregate investment return R_{t+1}^I

$$R_{t+1}^I = a + \Gamma X_t + U_{t+1} \quad (7)$$

The aggregate investment return R_{t+1}^I is measured as the continuously compounded quarterly growth rate in gross private domestic investment. Cochrane (1991, 1996) shows that aggregate investment returns can be approximated by investment growth rate without any misrepresentation of the model. Our vector of aggregate variables X_t includes variables that are known to forecast aggregate investment returns such as the growth rate of industrial production IP_t , the term spread TP_t , the default spread DP_t , and the aggregate stock market return MKT_t .⁷

⁷ An incomplete list of papers motivating our variables includes Chen, Roll, and Ross (1986), Cochrane (1991), Petkova and Zhang (2005), and Cooper and Priestley (2011). There are two reasons for choosing these variables. First, these variables have been found in the previous literature to be the most reliable predictors for aggregate investment returns (Cochrane, 1991). Second, these variables are known in the literature to have a common business cycle component. For example, much of the previous research lends support to the growth rate of industrial production as a highly pro-cyclical macroeconomic variable (Cooper and Priestley, 2011). In addition, the term spread is found to be a main leading indicator of macroeconomic activity (i.e., it falls prior to recessions) (Petkova and Zhang, 2005; Cooper and Priestley, 2011; Nyberg, 2012). Furthermore, the default spread reflects news about aggregate default probabilities and the market's expectations of future cash flows (Campbell, Giglio, and Polk, 2013). Similar to the term spread, the aggregate stock market return is a leading economic indicator of recessions since stock prices are forward looking and reflect expectations of future macroeconomic activity (Cochrane, 1991; Cooper and Priestley, 2011).

After estimating the VAR model, we use the VAR parameter estimates to decompose aggregate investment returns into unpredictable (CF) and predictable (DR) components. Applying Campbell and Shiller (1988) variance decomposition framework, we decompose the unexpected investment return r_{t+1}^I into CF and DR news⁸

$$r_{t+1}^I - E_t[r_{t+1}^I] = N_{CF,t+1}^I - N_{DR,t+1}^I \quad (8)$$

where E_t denotes an expectation formed at the end of period t . The expected aggregate investment return news $N_{DR,t+1}^I$ can be expressed as

$$N_{DR,t+1}^I = \lambda' U_{t+1} \quad (9)$$

where $\lambda' = e_1' \rho \Gamma (I - \rho \Gamma)^{-1}$; e_1' is a vector with the first element equal to one and the remaining elements equal to zero (i.e., $e_1' = [1 \ 0 \ 0 \ \dots \ 0]$); Γ is the estimated VAR transition matrix, and ρ is set equal to 0.95, as in Campbell and Vuolteenaho (2004). Equation (9) models the discount rate news as a linear function of the $t+1$ shock vector, so that the greater the ability of the VAR state variables (in the first row of the VAR matrix) to predict investment return, the

⁸ Drawing on the analogy between investment and stock returns, we assume that there is a non-linear relation between the shadow price of capital q_t and investment returns R_t^I . Thus, we follow Campbell and Shiller (1988) and achieve linearity by estimating a log-linear present value relation between capital prices and marginal productivity of capital. First, we take the logarithm of investment return in equation (5) and define r_t^I as the log aggregate investment return

$$r_t^I \equiv \log(mpk_t + (1 - \delta_{t+1})q_{t+1}) - \log(q_{t+1})$$

For expositional clarity, we use more compact notation by defining the marginal productivity of capital as $mpk_t = (\partial \pi(K_{t+1}) / \partial K_{t+1}) - (\partial \phi(I_{t+1}, K_{t+1}) / \partial K_{t+1})$. Second, we achieve linearity between the shadow price of capital q_{t+1} and marginal productivity of capital mpk_t by using a first-order Taylor expansion to approximate log investment returns r_t^I around its mean. If we substitute the first-order Taylor approximation, we get

$$r_t^I \approx k + ((1 - \rho) \log(mpk_t)) + ((\rho) \log(1 - \delta_{t+1})q_{t+1}) - \log(q_{t+1})$$

Where k and ρ are linearization parameters defined by $k \equiv -\log(\rho) - (1 - \rho) \log(1/\rho - 1)$ and $\rho \equiv 1/(1 + e^{\log(mpk_t) - \log(q_{t+1})})$. The log investment return is defined now as a weighted average of the marginal productivity of capital and the liquidation value net of depreciation. If we assume that $\lim_{i \rightarrow \infty} E_t \rho (1 - \delta_{t+1})q_{t+1} = 0$, where E_t denotes an expectation formed at the end of period t , and solve for $\log q_t$, we can write capital prices as linear combination of expected marginal product of capital and returns

$$\log(q_t) \equiv \frac{k}{1 - \rho} + (1 - \rho) E_t \left[\sum \rho mpk_t \right] - E_t \left[\sum \rho r_t^I \right]$$

Similar to Campbell (1991), we use the log-linear present value approach to write investment returns as linear combination of revisions in expected marginal productivity of capital and returns. This decomposes the unexpected investment return or the investment return innovation into cash flow and discount rate news

$$r_t^I - E_t[r_t^I] = (E_{t+1} - E_t) \{ \sum \rho mpk_t - \sum \rho r_t^I \} = N_{CF,t}^I - N_{DR,t}^I$$

higher the predictable component in the investment return, and consequently, the greater the DR news. Once we calculate DR news, aggregate CF news $N_{CF,t+1}^I$ can be computed directly as residuals

$$N_{CF,t+1}^I = (e1' + \lambda')U_{t+1} \quad (10)$$

As with other studies employing VAR estimates to decompose returns into DR and CF components, an alternative perspective is to view our decomposition as being between the predictable and unpredictable components of returns, which may not necessarily correspond to DR and CF components (Chen and Zhao, 2009). We find it more useful to frame our procedure in terms of DR and CF components, although recasting our procedure according to the perspective of Chen and Zhao would also be valid. While the conceptual framework of Chen and Zhao provides an alternative way to interpret our analysis, the empirical procedures laid out by Chen and Zhao cannot be directly applied to our analysis of firm-level investment returns.

The main proposition of any production-based model is that a stock's riskiness can be measured by the covariance of the stock's returns with the marginal rate of transformation, proxied by the investment return (when measurable) or the investment growth rate. The empirical formulation of the standard production based models (e.g., Cochrane, 1991 and 1996; Lamont, 2000; Li, Vassalou, and Xing, 2006; Liu, Whited, and Zhang, 2009) is to regress stock returns $r_{i,t+1}^E$ on aggregate investment returns R_{t+1}^I as follows

$$r_{i,t+1}^E = \alpha + \beta^I R_{t+1}^I + \varepsilon_{i,t+1} \quad (11)$$

We use the superscript E to distinguish stock returns from investment returns. We expand equation (11) by regressing stock returns on the two components of aggregate investment returns – aggregate cash flow (CF) $N_{CF,t+1}^I$ and aggregate discount rate (DR) $N_{DR,t+1}^I$ news

$$r_{i,t+1}^E = \alpha + \beta_{i,CF}^I N_{CF,t+1}^I + \beta_{i,DR}^I N_{DR,t+1}^I + \varepsilon_{i,t+1} \quad (12)$$

These estimates of aggregate CF and DR investment news allow us to parse the sensitivity of firm-level stock returns relative to the aggregate investment return news into two betas – aggregate CF investment beta and aggregate DR investment beta

$$\text{Aggregate CF investment beta, } \beta_{i,CF}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E, N_{CF,t+1}^I)}{\text{Var}_t(R_{t+1}^I)} \quad (13)$$

$$\text{Aggregate DR investment beta, } \beta_{i,DR}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E - N_{DR,t+1}^I)}{\text{Var}_t(R_{t+1}^I)} \quad (14)$$

The aggregate CF investment beta $\beta_{i,CF}^I$ is defined as the covariance between the stock returns and the CF component of aggregate investment return news $N_{CF,t+1}^I$, and it measures the sensitivity of stock returns to the shocks coming from the fundamental marginal productivity of capital. The aggregate DR investment beta $\beta_{i,DR}^I$ is defined as the covariance between a firm's stock returns $r_{i,t+1}^E$ and the DR component of aggregate investment return news $N_{DR,t+1}^I$. Several studies have decomposed the aggregate stock market return into CF and DR components (e.g., Campbell and Vuolteenaho, 2004; Campbell, Polk, and Vuolteenaho, 2010; Garrett and Priestley, 2012). Our approach differs in the sense that we are decomposing based on news about aggregate investment returns.

3.3 Hypotheses Testing: Downside CF and DR Betas

The essence of our empirical work is to evaluate the effects of *aggregate* CF and DR investment news on stock returns during down-market conditions.⁹ To this end, we estimate the

⁹ The traditional Capital Asset Pricing Model (CAPM) is based on the assumption of symmetric risk. This means that a security's expected excess return is proportional to its market beta, which is constant across periods of declining and rising markets. However, there is convincing evidence in the literature supporting the notion of the asymmetric pricing of downside risk and upside risk, which reflects the tendency of securities to move downward in a declining market more than they move upward in a rising market (Ang et al., 2006; Botshekan, Kraeussl, and Lucas, 2012). A motivation for the asymmetric treatment of risk is based on the principle of loss aversion (i.e., investors are more sensitive to downside losses relative to upside gains) which has been consistently documented through studies of prospect theory (Kahneman and Tversky, 1979).

sensitivity of stock returns $r_{i,t+1}^E$ to aggregate CF investment news $N_{CF,t+1}^I$ and aggregate DR investment news $N_{DR,t+1}^I$ in down markets as follows

$$\text{Downside aggregate CF investment beta } \beta_{i,CF,D}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E, N_{CF,t+1}^I) | R_{t+1}^M < 0}{\text{Var}_t(R_{t+1}^I) | R_{t+1}^M < 0} \quad (15)$$

$$\text{Downside aggregate DR investment beta } \beta_{i,DR,D}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E - N_{DR,t+1}^I) | R_{t+1}^M < 0}{\text{Var}_t(R_{t+1}^I) | R_{t+1}^M < 0} \quad (16)$$

We define downside aggregate CF beta $\beta_{i,CF,D}^I$ and downside aggregate DR beta $\beta_{i,DR,D}^I$ over time by conditioning a stock's return $r_{i,t+1}^E$ covariation with aggregate CF investment news $N_{CF,t+1}^I$ and aggregate DR investment news $N_{DR,t+1}^I$, respectively, when aggregate market return R_{t+1}^M is negative.¹⁰ The closest work to our description above is Botshekan, Kraeussl, and Lucas (2012), but our paper is different in the sense that we focus on decomposing news about investment returns, rather than market returns.

We expand the standard production-based models by incorporating the asymmetric exposure of high versus low-investment firms to CF and DR channels during market downturns. More specifically, the sensitivity of low-investment firms' stock returns to aggregate cash flow investment news, $N_{CF,t+1}^I$, and to aggregate discount rate investment news, $N_{DR,t+1}^I$, during market downturns is given by

$$r_{i,t+1}^E = \alpha + \beta_{i,CF,D}^{I,Low} N_{CF,t+1}^I + \beta_{i,DR,D}^{I,Low} N_{DR,t+1}^I + \varepsilon_{i,t+1} \quad (17)$$

where $\beta_{i,CF,D}^{I,Low}$ and $\beta_{i,DR,D}^{I,Low}$ are the low-investment firms' downside aggregate CF and DR betas, respectively. Similarly, the high-investment firms' risk exposure to the aggregate CF and DR news during down markets is given by

$$r_{i,t+1}^E = \alpha + \beta_{i,CF,D}^{I,High} N_{CF,t+1}^I + \beta_{i,DR,D}^{I,High} N_{DR,t+1}^I + \varepsilon_{i,t+1} \quad (18)$$

¹⁰ We use different measures for downside risk (measures defined relative to median or average market returns) and they yield similar results.

where $\beta_{i,CF,D}^{I,High}$ and $\beta_{i,DR,D}^{I,High}$ are the high-investment firms' downside aggregate CF and DR betas, respectively. Equations (17) and (18) are the empirical formulation of our testable hypotheses, which state that both high- and low-investment firms differ in their sensitivity to aggregate CF and DR investment news that serve as a source of systematic risk. The productivity constraints hypothesis states that stock returns of low-investment firms are more sensitive to downside CF news about investment returns relative to high-investment firms (i.e., $\beta_{i,CF,D}^{I,Low} > \beta_{i,CF,D}^{I,High}$). The financing constraints hypothesis states that stock returns of high-investment firms are more sensitive to downside CF news about investment returns relative to high-investment firms (i.e., $\beta_{i,DR,D}^{I,Low} < \beta_{i,DR,D}^{I,High}$).

3.4 Firm-level Analysis

To further check our findings from the aggregate-level analysis, we also run our estimations using firm-level data. The literature on real option models focuses on the link between firm-specific investment patterns and the cross section of stock returns (Berk, Green, and Naik, 1999; Gomes, Kogan, and Zhang, 2003; Carlson, Fisher, and Giammarino, 2004). Our goal is to examine whether firm-specific stock return risk premia reflect news about their cash flows and/or whether they are associated with news about discount rates that investors apply to those cash flows. Thus, we look separately at the CF and DR shocks to firm-level investment. To this end, we use the following firm-level first-order VAR model to decompose firm-level investment returns as follows

$$R_{i,t+1}^I = a + \Gamma \begin{bmatrix} Z_{i,t} \\ X_t \end{bmatrix} + u_{i,t+1} \quad (19)$$

The investment growth rate of firm i $R_{i,t+1}^I$ is our variable of interest, since we use it as a proxy for the firms' investment returns. In addition, firm-level investment growth is subject to both

firm-specific variables $Z_{i,t}$ as well as aggregate variables X_t . Our vector of firm-level investment growth rate predictors $Z_{i,t}$ includes two variables – book-to-market BE/ME and asset size TA . We use book-to-market and asset size to proxy for the discount rate and the financing constraints, respectively.¹¹ The rationale for including aggregate variables X_t in the VAR model is to allow macroeconomic variables to affect firm-level investment decisions. Since there is minimal feedback from firm-level variables to aggregate variables, we constrain the lower left corner of matrix Γ to zero.

We follow the same approach as in the aggregate analysis and decompose firm-level specific investment returns $R_{i,t+1}^I$ into firm-level CF news $N_{CFi,t+1}^I$ and DR news $N_{DRi,t+1}^I$. These two approximated firm-level channels allow us to examine separately the firms' stock returns sensitivity to CF and DR components of the firm-level investment returns as follows

$$\text{Firm-level CF investment beta } \beta_{i,CFi}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E, N_{CFi,t+1}^I)}{\text{Var}_t(R_{i,t+1}^I)} \quad (20)$$

$$\text{Firm-level DR investment beta } \beta_{i,DRi}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E, -N_{DRi,t+1}^I)}{\text{Var}_t(R_{i,t+1}^I)} \quad (21)$$

The firm-level CF investment beta $\beta_{i,CFi}^I$ is defined as the covariance between the firm's stock returns and the CF component of *firm-level* investment returns. The firm-level DR investment beta $\beta_{i,DRi}^I$ is defined as the covariance between the firm's stock returns $r_{i,t+1}^E$ and the DR component of the *firm-level* investment returns. Campbell and Mei (1993) decompose the firm-level stock returns into CF and DR components, but our approach differs in the sense that we are decomposing based on news about firm-level investment returns.

¹¹ Zhang (2005) shows that value firms exhibit lower capital investment than growth firms since they have a more unproductive capital stock. One might expect, therefore, that growth firms (low BE/ME) invest the most since a greater fraction of their value consists of growth options. Additionally, we follow Gilchrist and Himmelberg (1995) and Li and Zhang (2010) in using asset size as a firm-level proxy of financing constraints, since young and less well-known firms typically have fewer assets and consequently are more financially-constrained than well-known firms with greater assets.

We then estimate the sensitivity of stock returns $r_{i,t+1}^E$ to *firm-level* CF investment news $N_{CF,i,t+1}^I$ and *firm-level* DR investment news $N_{DR,i,t+1}^I$ in down markets as follows

$$\text{Downside firm-level CF investment beta } \beta_{i,CF,D}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E, N_{CF,i,t+1}^I) | R_{t+1}^M < 0}{\text{Var}_t(R_{t+1}^I) | R_{t+1}^M < 0} \quad (22)$$

$$\text{Downside firm-level DR investment beta } \beta_{i,DR,D}^I \equiv \frac{\text{Cov}_t(r_{i,t+1}^E - N_{DR,i,t+1}^I) | R_{t+1}^M < 0}{\text{Var}_t(R_{t+1}^I) | R_{t+1}^M < 0} \quad (23)$$

4. Data, Variable Definitions, and Summary Statistics

Our data set consists of quarterly aggregate data as well as quarterly firm-level data. Although aggregate data is available from the first quarter of 1963 until the fourth quarter of 2013, firm-level data on investment growth rates is available only from the first quarter of 1985. We exclude financial firms (i.e., firms in finance, insurance and real estate), closed-end funds, trusts, ADRs, and REITs, due to the difficulty of interpreting their capital investment which is our major focus in this study. In order to be consistent with other studies of investment returns, we include only firms in the manufacturing sector, defined as those with primary standard industrial classifications (SIC) between 2000 and 3999.

Our main variable of interest is investment returns, measured both at aggregate and firm-levels. We measure aggregate investment return R_{t+1}^I by the growth rate in gross private domestic investment from the Fed's FRED database, and we measure our firm-specific investment return $R_{i,t+1}^I$ by the growth rate in the firm-specific capital expenditures IG from COMPUSTAT. These two measures of investment growth rate are entered into two different VAR models, and therefore yield different estimated values for CF and DR news components.

The aggregate CF and DR investment news ($N_{CF,t+1}^I$ and $N_{DR,t+1}^I$) are computed from the aggregate VAR model defined by equation (7) using a vector of 5 aggregate variables X_t - aggregate investment growth rate IR , the growth rate of industrial production index IP , the term

premium TP , the default premium DP , and the aggregate value-weighted stock return MKT . IR is measured as the continuously compounded quarterly growth rate in gross private domestic investment; IP is calculated as the percentage change in the index of industrial production (as in Chen, Roll, and Ross, 1986; Liu and Zhang, 2008; Cooper and Priestley, 2011); TP is defined as the yield spread between the long-term (ten-year) government bond yields minus the short-term (three-month) Treasury bill yield; DP is calculated as the difference between the yields on Moody's Baa and Aaa seasoned corporate bond indices; MKT is the excess returns on the CRSP value-weighted stock index over the risk-free rate (proxied by the T-Bill yield with three months to maturity) (Campbell, Giglio, and Polk, 2013). Data on the aggregate economic variables are obtained from the St Louis Fed's FRED database and the National Income and Product Accounts (NIPA) published by the Federal Reserve System. All aggregate variables are measured as the natural log of (1 plus) quarterly returns or yields. Figure (1) plots the cumulative values of these aggregate predictor variables over our sample period.

[Insert Figure (1) Here]

The firm-level CF and DR investment news ($N_{CFi,t+1}^I$ and $N_{DRi,t+1}^I$) are computed from the firm-level VAR model defined by equation (19) that includes firm-specific predictor variables in addition to aggregate ones. Our vector of firm-level predictors $Z_{i,t}$ includes book-to-market BE/ME and asset size TA . Size is measured by the book value of total assets TA . We use the book value of Total Assets to capture the physical size of the firm in order to avoid the potential endogeneity of market values of size with regard to our estimates of returns. The book value of equity BE is computed as the sum of the book value of common equity, deferred taxes and investment tax credits, minus the book value of preferred stock. We obtain quarterly financial statement and balance sheet data from COMPUSTAT, and stock return $r_{i,t}^E$ and market

capitalization data from the Center for Research in Security Prices (CRSP). Table (1) presents the descriptive statistics of these firm-specific variables. The stock returns, firm-level investment growth rates, book-to-market ratios, and sizes of our sample firms are comparable to those in other studies.

[Insert Table (1) Here]

Figure (2) displays these quarterly aggregate and average firm-level CF and DR news components of investment growth rates over our sample period. Although table (1) shows that the signs are different for our aggregate and average firm-specific news, we do observe many similar patterns across the two measures in figure (2), suggesting that they do both capture slightly different aspects of the same process. We do not focus on a direct numerical interpretation of the raw measures of aggregate and firm-level CF and DR news, as this is provided in other papers (e.g., Campbell and Vuolteenaho, 2004). Instead we focus on firms' stock return sensitivity (i.e., 'beta' coefficients in a regression of returns on CF and DR news), as reported in the following tables.

[Insert Figure (2) Here]

We focus on two investment-based variables known to capture the cross-section of average stock returns.¹² Our first measure of investment is the asset growth rate (denoted as *AG*) developed by Cooper, Gulen, and Schill (2008) and then used by several studies to proxy for firm-level investment return (e.g., Cooper and Priestley, 2011; Lam and Wei, 2011; Watanabe et al., 2013; Huang and Wang, 2014). We estimate each firm's *AG* as the year-on-year percentage change in quarterly total assets (denoted as *TA*). Our second measure of investment is the investment growth rate (*IG*). Similar to previous studies (e.g., Titman, Wei, and Xie, 2004; Xing, 2008, Prombutr, Phengpis and Zhang, 2012), we measure *IG* as the year-on-year growth rate of

¹² For a review on the measures of investment returns, see Cooper and Priestley (2011).

quarterly capital expenditures for firms with non-negative capital expenditures. We require valid data for *IG*, *AG*, *BE*, and returns, as well as *TA* greater than \$10 million for a firm to be included in our sample.

The investment effect refers to the empirical finding that companies that grow their total assets more or invest more earn lower subsequent average stock returns. Figure (3) displays average values for these investment variables (*AG* and *IG*) in addition to average stock returns over the period from 1985 to 2013. Our computations of *AG* over time are consistent with those reported by Cooper, Gulen, and Schill (2008). Additional checks (not reported) confirm that our sample displays a similar (i.e., negative) association between *AG* and stock returns as reported by Cooper, Gulen, and Schill (2008) for the time frame where our studies overlap (up until 2002). Our expanded sample period from 2002 to 2013 displays interesting additional variation in investment levels and returns that is not included in the Cooper, Gulen, and Schill (2008) study or other earlier studies.

[Insert Figure (3) Here]

5. Empirical Results

This section presents the empirical results of testing both the productivity constraints hypothesis and the financing constraints hypothesis. Our goal is to test for patterns in the behavior of the investment-stock return relation (driven by CF and DR news) during market downturns. We sort firms into portfolios employing both single independent sorts and double sorts by our two investment-based variables (*AG* and *IG*) and size. As is common in other studies, we include firm size *TA* as a control variable. We estimate the CF and DR investment betas conditional on the state of the market for single and double sorted portfolios, and then we

evaluate our hypotheses by examining how firms differ in their sensitivity to downside CF and DR news across levels of investment.

5.1 Results of Testing H1: Productivity Constraints and Downside CF Betas

We start by evaluating the predictions of our productivity constraints hypothesis. To test our first hypothesis, we compare loadings with respect to the portfolios for the CF news across all market conditions and for the CF news during market downturns for top and bottom AG (and IG) portfolios. Our productivity constraints hypothesis states that stock returns of low-investment firms should be more sensitive to downside CF news about investment returns than are high-investment firms. If that is the case, then we should observe higher values for the downside CF betas estimates for the bottom quintile(s) based on AG or IG levels compared to the top quintile(s).

Tables (2) and (3) present two variants to test the productivity constraints hypothesis using aggregate and firm-level data, respectively. Table (2) presents the coefficient estimates of aggregate CF investment betas $\beta_{i,CF}^I$ estimated from equation (13), and downside aggregate CF investment betas $\beta_{i,CF,D}^I$ estimated from equation (15). Table (3) displays the coefficient estimates of firm-level CF investment betas $\beta_{i,CFi}^I$ estimated from equation (20), and downside firm-level CF investment betas $\beta_{i,CFi,D}^I$ estimated from equation (22). In both tables, panel (A) presents the results of single-sorted portfolios formed based on independent sorts by firm-level asset growth AG, investment growth IG, and size TA, and panel (B) displays the results for double-sorted portfolios sorted first by size and then by AG and IG. We are primarily concerned with the overall scale of the sensitivity of portfolio returns to news about aggregate CF and downside CF news, and we thus report the absolute value of the coefficient estimates for each quintile portfolio.

Table (2) provides the estimates of aggregate CF betas $\beta_{i,CF}^I$ and downside aggregate CF betas $\beta_{i,CF,D}^I$ for portfolios sorted by our two investment-based variables (*AG* and *IG*) and size. For aggregate CF betas, the results in panel (A) show that the sensitivity of stock returns to aggregate CF investment news is generally decreasing with firm size. The results for double-sorted portfolios presented in panel (B) show that the sensitivity to aggregate CF investment news is different for portfolios of small and large firms. Large firms generally have an increasing sensitivity to CF news as *AG* increases, while the association between *AG* and sensitivity to CF news is U-shaped for small firms. Firms in the 4th quintile of investment growth *IG* display the strongest sensitivity to CF news, with the sensitivity being much stronger for small firms. For downside aggregate CF betas, the results in panel (A) suggest that the coefficient estimates are U-shaped with respect to both *AG* and *IG*. However, the results presented in panel (B) indicate that there is a strong monotonic relationship between levels of investment growth and sensitivity to downside CF news for large firms. These results suggest that large firms face more constraints in production, as investment growth (*IG*) increases.

If our productivity hypothesis is correct, then we should observe higher values for the downside CF betas estimates for the bottom quintile(s) based on *AG* or *IG* levels compared to the top quintile(s). Two points from table (2) are particularly noteworthy. First, we observe a pattern consistent with our productivity hypothesis, but only for firms sorted by total asset growth *AG*. Panel (A) shows that the loadings with respect to the portfolio for CF information during market downturns are higher for the low *AG* portfolio than for the high *AG* portfolio. Second, our productivity constraints hypothesis is more accurate in explaining the returns of small firms than large firms. Panel (B) shows that small firms with less *IG* or *AG* are more sensitive to aggregate CF news in downside conditions, while large firms display the opposite pattern. Large firms are

more sensitive to aggregate CF news when they have more *AG* or *IG*, regardless of market conditions. Overall, these results are consistent with our productivity hypothesis with respect to aggregate CF news, but only for small firms.

[Insert Table (2) Here]

Table (3) presents the results of testing the productivity constraints hypothesis using firm-level data. The reported firm-level betas in table (3) represent the equally-weighted average betas for firms in each investment-level portfolio. For firm-level CF betas $\beta_{i,CFi}^I$, panel (A) of table (3) shows that the sensitivity to CF news generally declines for firms with more investment growth but generally increases with asset growth. There is no clear pattern across quintiles based on size. Panel (B) allows for a more precise evaluation of these patterns by displaying the results for portfolios sorted first by size and then by *IG* or *AG*. The most apparent pattern is that the sensitivity to CF news declines with higher levels of asset growth for both small and large firms. There is a strong inverted-U-shaped pattern between levels of investment growth and CF news for large firms. The differences in Table (3) for sorts based on *IG* and *AG* imply that the components of total assets other than capital expenditures have a meaningful association with news about investment growth rates. For downside firm-level CF betas $\beta_{i,CFi,D}^I$, panel (A) of table (3) suggests that firm size is more relevant than either asset growth or investment growth in evaluating potential productivity constraints. The large-firm quintiles display much greater sensitivity to downside news about CFs. The sensitivities of high-investment and low-investment firms to CF information across all market conditions is similar with respect to firm-level information in table (3) as they were for aggregate information in table (2).

We find results consistent with our productivity constraints hypothesis but only for *IG* sorted portfolios. In panel (A) of table (3), downside sensitivities to firm-level information are

stronger for firms with lower levels of IG . When we consider firms sorted by size and IG in panel (B), we find a supporting pattern but only for small firms sorted by IG in downside conditions. However, patterns are erratic across levels of AG for downside firm-specific information. We find that small firms with higher levels of total asset growth AG display greater sensitivity to downside firm-specific CF news. The results of testing our productivity constraints hypothesis based on firm-level CF information in table (3) are different from those extracted from market-wide information in table (2), indicating that the incorporation of firm-specific information about downside CFs can lead to very different conclusions than models which rely only on market-wide information.

[Insert Table (3) Here]

5.2 Results of Testing H2: Financing Constraints and Downside DR Betas

We then empirically investigate the predictions of our financing constraints hypothesis that states that stock returns of high-investment firms should be more sensitive to downside DR news about investment returns than are low-investment firms. If our financing hypothesis is correct, then we should observe higher values for the downside DR betas estimates for the top quintile(s) based on AG or IG levels compared to the bottom quintile(s).

To test the financing hypothesis, we compare DR betas across all market conditions to DR betas during market downturns, both at aggregate and firm levels. Table (4) presents the coefficient estimates measuring the sensitivity of portfolio returns to estimated DR news about aggregate investment growth rates $\beta_{i,DR}^I$ using equation (14), and to estimated downside DR news about aggregate investment growth rates $\beta_{i,DR,D}^I$ using equation (16). Table (5) displays the

coefficient estimates of firm-level DR investment betas $\beta_{i,DRi}^I$ estimated from equation (21), and downside firm-level DR investment betas $\beta_{i,DRi,D}^I$ estimated from equation (23).

Table (4) validates the results of testing the second hypothesis using aggregate-level data. For aggregate DR betas $\beta_{i,DR}^I$, panel (A) indicates that the sensitivity to DR investment news is generally decreasing with size, but with a U-shaped pattern. The results for double-sorted portfolios presented in panel (B) show that large firms generally have an increasing sensitivity to DR news as asset growth increases. For downside aggregate DR betas $\beta_{i,DR,D}^I$, the results in panel (A) suggest that DR betas are U-shaped with respect to both *AG* and *IG*. However, the results presented in panel (B) indicate that there is an association between levels of investment growth and sensitivity to downside DR news for large firms, but is not monotonic.

If our financing constraint hypothesis is accurate in capturing the association between investment growth rates and risk sensitivities to investment news, then we should observe higher values for the coefficient estimates for the top quintile(s) based on *IG* or *AG* levels compared to the bottom quintile(s). Two points from table (4) are particularly noteworthy. First, panel (A) indicates that there exists a complex association between potential financing constraints reflected in aggregate DR information and firm-specific investment levels. Across all market conditions, firms with higher levels of *AG*, but lower levels of *IG*, are more sensitive to DR information. In downside conditions, however, the opposite pattern holds, as firms with lower levels of *AG* but higher levels of *IG* are more sensitive to DR news. Second, our results are consistent with our financing hypothesis with respect to aggregate DR news, but only for large firms. When firm size is considered in panel (B), this helps to clarify the opposite patterns observed in panel (A). In particular, we observe that small firms display higher values for the coefficient estimates for the bottom quintile(s) based on *IG* and *AG* levels compared to the top quintile(s). However, large

firms display increasing sensitivities to DR news as investment levels increase, both across all market conditions and specifically during downturns. Therefore, our results are consistent with large firms displaying an association between financing constraints and higher investment levels, as implied by our financing constraints hypothesis.

[Insert Table (4) Here]

Table (5) shows the results of testing our second hypothesis using firm-specific information. For firm-level DR betas $\beta_{i,DRi}^I$, panel (A) shows that the sensitivity to DR news generally declines for firms with more investment growth IG but generally increases with asset growth AG . Panel (B) in table (5) shows that sensitivity of portfolio returns to DR investment news declines with higher levels of assets growth AG for both small and large firms. There is a strong inverted-U-shaped pattern between levels of investment growth and both CF and DR news for large firms. For downside firm-level DR Betas $\beta_{i,DRi,D}^I$, we observe stronger sensitivities as IG increase for large firms. Again, for small firms the increased sensitivity is more apparent across levels of total asset growth AG .

Similar to table (3), the results from table (5) suggest that the incorporation of firm-specific news leads to different conclusions than do estimates based only on aggregate news. Panel (B) in table (5) indicates that both small and large firms display increasing sensitivity to DR news for portfolios with the highest levels of AG . However, the sensitivity for firms sorted by IG peaks at quintile 4 and then declines, making the association for this variable difficult to evaluate. As with aggregate information, downside coefficient estimates show that the sensitivity to DR news for small firms is highest for the low-investment portfolios. For large firm, the sensitivity to DR news is clearly highest for firms in the top quintiles of IG , but peaks at quintile 4 for AG . Overall, these results suggest that potential financing constraints, represented by

increased sensitivity to DR news for firms with highest levels of investment, are much more accurate in characterizing the returns of large firms in downside conditions than small firms.

[Insert Table (5) Here]

6. Conclusions

Our analysis provides several useful new results about the investment effect. First, CF and DR investment news derived from firm-level information is distinct from aggregate news and displays much more variation across firms with different levels of capital investment. Second, we show that firm size is more important than investment levels in explaining sensitivity to both CF and DR aggregate news, with small firms being the most sensitive. Third, firms' responses to downside investment news are distinct from their unconditional responses to investment news across all market conditions. Fourth, we find our productivity constraints hypothesis to be a useful explanation for the sensitivity of small firms to news about investment CF news. Last, our financing constraints hypothesis is accurate in explaining the sensitivity of large firms to news about investment DR news.

When one considers the production side, firm size is far more relevant than either asset growth or investment growth in evaluating potential productivity constraints regarding firm-level investment news about CFs. This is consistent with the Q-theory framework of productivity in which firms face capacity constraints as scale increases. However, it illustrates the difficulty of using this framework to link investment levels with these productivity constraints. Firm size appears to be a more useful proxy for investment constraints than more precise accounting-based measures such as the growth in total assets or capital expenditures. Overall, our tests find patterns that are consistent with the implications of Q-theory as applied to productivity constraints and investment levels, but only for small firms.

When the financing side is considered, Q-theory suggests that firms are more likely to face financing constraints during market downturns when these firms have higher levels of investment growth. Our results are consistent with this prediction, but only for large firms. This motivates a limited evaluation of the association between capital expenditures and the investment effect, in that these higher-risk, high-investment firms should entail lower demand from investors and thus earn a corresponding a risk premium. However, this is a partial explanation at best for the investment effect and illustrates the need for the development and testing of more precise models of how the potential productivity and financing constraints of firms are determined by firm size and investment levels. Our work takes one step in refining and testing existing models to include investment level, firm size, and market conditions, while our results indicate that there are several potential paths for future research to take in further exploring these relationships.

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Table 1: Descriptive Statistics of Variables

This table presents descriptive statistics of our sample of quarterly firm-level financial data. The sample consists of 133,216 firm-quarters drawn from 1,841 unique firms over the period from Q1 1985 until Q4 2013. Stock returns are the average quarterly stock returns for sample firms. Investment Growth (*IG*) is the year-on-year growth rate in quarterly capital expenditures for firms with non-negative capital expenditures. Size is measured by the book value of total assets and asset growth (*AG*) is the percentage quarterly change in firm size. The book value of equity (*BE*) is computed as the sum of the book value of common equity, deferred taxes and investment tax credits, minus the book value of preferred stock. Firm-level investment CF and DR news are computed from a VAR model that includes firm-specific predictor variables in addition to aggregate ones. Aggregate investment DR and CF news are computed from a VAR model using 5 macro-economic predictor variables for aggregate investment growth.

	Mean	Median	Standard Deviation
Stock Returns	4.78%	2.91%	27.38%
Investment Growth (IG)	1.95%	2.08%	23.07%
Asset Growth (AG)	2.54%	1.42%	11.75%
Size (millions)	\$4,779,366	\$560,817	\$20,164,233
Book-to-market Ratio	64.06%	50.26%	61.35%
Firm-level CF News	-0.32%	-0.27%	0.01
Firm-level DR News	-0.16%	-0.09%	0.01
Aggregate CF News	3.94%	2.14%	1.63
Aggregate DR News	2.06%	1.19%	0.89

Table 2: Sensitivities to Aggregate CF Investment News

This table provides estimates of the sensitivity of portfolio stock returns to estimated cash flow (CF) news about *aggregate* investment growth rates, $\beta_{i,CF}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *aggregate* investment returns. The table also presents estimates of the downside sensitivity of portfolio stock returns to estimated cash flow (CF) news about *aggregate* investment growth rates, $\beta_{i,CF,D}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *aggregate* investment returns, conditional on market returns being negative in quarter t . Measures of aggregate CF news are extracted from a vector autoregression (VAR) model using 5 macroeconomic variables to forecast news about the CF and DR components of aggregate investment growth. Firms are sorted into equally-weighted quintile portfolios each quarter. Our sample consists of 92,117 firm-quarter observations over the period from Q1 1985 to Q4 2013 when market returns are negative. In Panel A, portfolios are sorted based on asset growth (AG) in columns 2 and 5, capital expenditures growth (IG) in columns 3 and 6, and based on firm size (TA) in columns 4 and 7. In Panel B, firms are first sorted by size, with results reported for portfolios from the top and bottom size groups, which are then sorted by AG or IG.

Panel A: Single sorts by AG, IG and Size

Quintile	<u>CF Betas</u> ($\beta_{i,CF}^I$)			<u>Downside CF Betas</u> ($\beta_{i,CF,D}^I$)		
	Ranked by:			Ranked by:		
	AG	IG	Size	AG	IG	Size
1	1.3205	2.1252	5.1064	5.1422	3.7883	3.4042
2	0.7525	0.4857	1.2273	3.1743	3.1319	2.9617
3	1.0815	1.3054	0.1240	1.6308	1.2121	4.3059
4	0.6081	1.9189	0.6680	2.4717	3.3709	3.2036
5	1.8329	0.6228	1.1637	3.8307	4.5367	3.2747

Panel B: Top and Bottom Quintiles by Size, and then sorted by AG and IG

Quintile	<u>CF Betas</u> ($\beta_{i,CF}^I$)				<u>Downside CF Betas</u> ($\beta_{i,CF,D}^I$)			
	Small Firms		Large Firms		Small Firms		Large Firms	
	Ranked by:		Ranked by:		Ranked by:		Ranked by:	
	AG	IG	AG	IG	AG	IG	AG	IG
1	5.6346	5.6611	0.5097	0.9832	7.4457	4.0799	2.8979	0.2937
2	3.3114	3.7363	0.0044	0.1512	0.3988	5.1697	2.8509	1.7195
3	4.5649	5.1598	0.4963	0.3969	1.9178	2.3943	3.6286	3.1389
4	4.0642	11.4157	1.3027	2.4426	1.4751	2.0428	3.6089	3.8577
5	6.8306	2.0553	2.2749	1.1058	3.5980	3.1117	3.3288	7.6802

Table 3: Sensitivities to *Firm-specific CF* Investment News

This table provides estimates of the sensitivity of portfolio stock returns to estimated cash flow (CF) news about *firm-level* investment growth rates $\beta_{i,CFi}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *firm-level* investment returns. The table also presents estimates of the downside sensitivity of portfolio stock returns to estimated cash flow (CF) news about *firm-level* investment growth rates, $\beta_{i,CFi,D}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *firm-level* investment returns, conditional on market returns being negative in quarter t . Measures of firm-level CF and DR news are extracted from a vector autoregression (VAR) model using 5 macroeconomic and 3 firm-specific variables to forecast news about the CF and DR components of investment growth. Firms are sorted into quintile portfolios each quarter. Our sample consists of 92,117 firm-quarter observations over the period from Q1 1985 to Q4 2013 when market returns are negative. In Panel A, portfolios are sorted based on the growth in total assets (AG) in columns 2 and 5, the growth in capital expenditures (IG) in columns 3 and 6, and based on firm size (TA) in columns 4 and 7. In Panel B, firms are first sorted by size, with results reported for portfolios from the top and bottom size groups, which are then sorted by AG or IG.

Panel A: Single sorts by AG, IG and Size:

Quintile	<u>CF Betas ($\beta_{i,CFi}^I$)</u>			<u>Downside CF Betas ($\beta_{i,CF,D}^I$)</u>		
	Ranked by:			Ranked by:		
	AG	IG	Size	AG	IG	Size
1	0.0991	0.2079	0.1144	0.0006	0.0150	0.0079
2	0.0432	0.0802	0.0074	0.0070	0.0269	0.0065
3	0.1318	0.0930	0.1507	0.0066	0.0204	0.0193
4	0.0944	0.1410	0.0935	0.0088	0.0146	0.0141
5	0.2176	0.0930	0.1198	0.0052	0.0084	0.0245

Panel B: Top and Bottom Quintiles by Size, and then sorted by AG and IG:

Quintile	<u>CF Betas ($\beta_{i,CFi}^I$)</u>				<u>Downside CF Betas ($\beta_{i,CF,D}^I$)</u>			
	Small Firms		Large Firms		Small Firms		Large Firms	
	Ranked by:		Ranked by:		Ranked by:		Ranked by:	
	AG	IG	AG	IG	AG	IG	AG	IG
1	0.2902	0.1944	0.1760	0.0345	0.0035	0.0240	0.0444	0.0006
2	0.1085	0.1407	0.1274	0.0674	0.0088	0.0055	0.0369	0.0147
3	0.0989	0.0852	0.0937	0.3600	0.0179	0.0456	0.0212	0.0484
4	0.0012	0.1027	0.1406	0.3090	0.0055	0.0045	0.0147	0.0345
5	0.0676	0.0904	0.0132	0.1024	0.0228	0.0092	0.0562	0.1147

Table 4: Sensitivities to Aggregate DR Investment News

This table provides estimates of the sensitivity of portfolio stock returns to estimated discount rate (DR) news about *aggregate* investment growth rates, $\beta_{i,DR}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *aggregate* investment returns. The table also presents estimates of the downside sensitivity of portfolio stock returns to estimated discount rate (DR) news about *aggregate* investment growth rates during downside, $\beta_{i,DR,D}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *aggregate* investment returns, conditional on market returns being negative in quarter t . Measures of aggregate DR news are extracted from a vector autoregression (VAR) model using 5 macroeconomic variables to forecast news about the CF and DR components of aggregate investment growth. Firms are sorted into equally-weighted quintile portfolios each quarter. Our sample consists of 92,117 firm-quarter observations over the period from Q1 1985 to Q4 2013 when market returns are negative. In Panel A, portfolios are sorted based on asset growth (AG) in columns 2 and 5, investment growth (IG) in columns 3 and 6, and based on firm size (TA) in columns 4 and 7. In Panel B, firms are first sorted by size, with results reported for portfolios from the top and bottom size groups, which are then sorted by AG or IG.

Panel A: Single sorts by AG, IG and Size:

Quintile	<u>DR Betas ($\beta_{i,DR}^I$)</u>			<u>Downside DR Betas ($\beta_{i,DR,D}^I$)</u>		
	Ranked by:			Ranked by:		
	AG	IG	Size	AG	IG	Size
1	2.9237	4.2915	9.3219	9.2963	8.2042	7.0661
2	2.3149	2.1582	3.6232	8.0235	6.5205	6.3513
3	3.0538	3.0896	1.1699	5.0237	4.0951	9.0370
4	2.4027	5.0081	2.5020	5.9856	7.5662	7.6363
5	4.4402	2.1072	4.0319	7.8268	8.9982	8.0242

Panel B: Top and Bottom Quintiles by Size, and then sorted by AG and IG:

Quintile	<u>DR Betas ($\beta_{i,DR}^I$)</u>				<u>Downside DR Betas ($\beta_{i,DR,D}^I$)</u>			
	Small Firms		Large Firms		Small Firms		Large Firms	
	Ranked by:		Ranked by:		Ranked by:		Ranked by:	
	AG	IG	AG	IG	AG	IG	AG	IG
1	9.2717	9.7197	3.0126	2.9088	12.1291	7.7627	7.9644	2.6110
2	6.4343	7.3984	1.9018	1.5473	0.6457	10.6938	8.2010	0.4622
3	9.0807	8.7331	2.5709	2.7641	6.8517	6.3443	8.9320	8.1681
4	8.5814	20.9953	4.4392	6.5280	3.8056	3.4031	10.7338	10.1780
5	12.0938	4.2060	5.9802	4.0354	7.8094	7.0142	5.0851	12.7421

Table 5: Sensitivities to *Firm-specific DR* Investment News

This table provides estimates of the sensitivity of portfolio stock returns to estimated discount rate (DR) news about *firm-level* investment growth rates, $\beta_{i,DRi}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *firm-level* investment returns. The table also presents estimates of the downside sensitivity of portfolio stock returns to estimated discount rate (DR) news about *firm-level* investment growth rates $\beta_{i,DRi,D}^I$, measured by the absolute values of coefficient estimates (“betas”) from OLS regressions of portfolio stock returns on CF and DR news about *firm-level* investment returns, conditional on market returns being negative in quarter t . Measures of firm-level CF and DR news are extracted from a vector autoregression (VAR) model using 5 macroeconomic and 3 firm-specific variables to forecast news about the CF and DR components of investment growth. Firms are sorted into quintile portfolios each quarter. Our sample consists of 92,117 firm-quarter observations over the period from Q1 1985 to Q4 2013 when market returns are negative. In Panel A, portfolios are sorted based on the growth in total assets (AG) in columns 2 and 5, the growth in capital expenditures (IG) in columns 3 and 6, and based on firm size (TA) in columns 4 and 7. In Panel B, firms are first sorted by size, with results reported for portfolios from the top and bottom size groups, which are then sorted by AG or IG.

Panel A: Single sorts by AG, IG and Size:

Quintile	<u>DR Betas ($\beta_{i,DRi}^I$)</u>			<u>Downside DR Betas ($\beta_{i,DR,D}^I$)</u>		
	Ranked by:			Ranked by:		
	AG	IG	Size	AG	IG	Size
1	0.3383	0.2596	0.4209	0.0055	0.0249	0.0169
2	0.1370	0.1280	0.1114	0.0097	0.0506	0.0136
3	0.1347	0.0781	0.2267	0.0146	0.0380	0.0365
4	0.0394	0.3229	0.0684	0.0090	0.0147	0.0261
5	0.3237	0.1792	0.1482	0.0135	0.0137	0.0272

Panel B: Top and Bottom Quintiles by Size, and then sorted by AG and IG:

Quintile	<u>DR Betas ($\beta_{i,DRi}^I$)</u>				<u>Downside DR Betas ($\beta_{i,DR,D}^I$)</u>			
	Small Firms		Large Firms		Small Firms		Large Firms	
	Ranked by:		Ranked by:		Ranked by:		Ranked by:	
	AG	IG	AG	IG	AG	IG	AG	IG
1	0.5748	0.1167	0.2564	0.0166	0.0071	0.0431	0.0823	0.0336
2	0.2942	0.2622	0.3341	0.3036	0.0080	0.0020	0.0676	0.0126
3	0.1954	0.1441	0.1477	0.6155	0.0361	0.0910	0.0762	0.0903
4	0.1225	0.0898	0.1547	0.5925	0.0112	0.0034	0.0182	0.0381
5	0.2202	0.1525	0.0058	0.1948	0.0444	0.0168	0.0957	0.1655

Figure 1: Macroeconomic Variables used to estimate CF and DR Components of Investment News

This figure displays compounded cumulative values of our 5 macro-economic variables that are used to estimate the CF and DR components of news about aggregate investment growth rates. The variables are: the aggregate investment growth rate (*IR*), the growth rate of industrial production (*IP*), the term premium (*TP*), the default premium (*DP*), and the aggregate value-weighted excess stock return (*MKT*). Quarter 4, 1984 equals 1 for each variable. *MKT* is measured on the right-axis while the other variables are measured relative to the left axis.

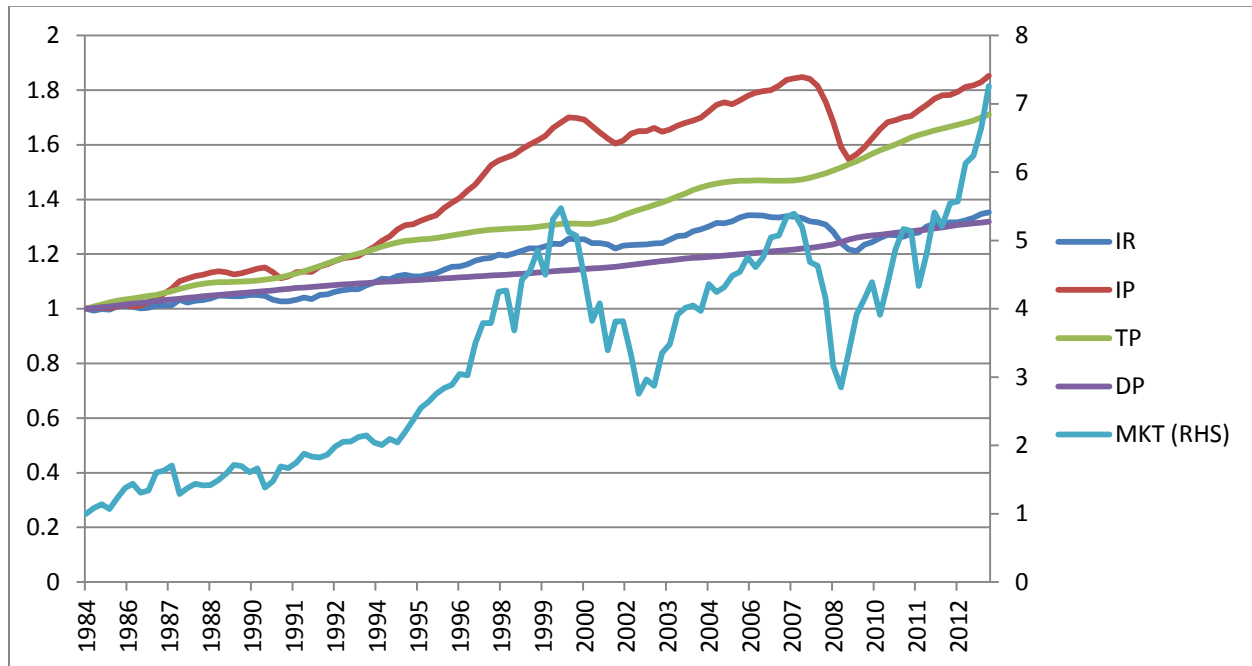


Figure 2: DR and CF News over time

This figure displays quarterly values of aggregate discount rate (DR) and cash flow (CF) news and average discount rate (DR) and cash flow (CF) news for individual stocks. Aggregate news components are measured by the left axis, while average levels of DR and CF news for individual stocks are measured by the right axis. Measures of aggregate CF and DR news are extracted from a vector autoregression (VAR) model using 5 macroeconomic variables to forecast news about the CF and DR components of aggregate investment growth. Measures of firm-level CF and DR news are extracted from a vector autoregression (VAR) model using 5 macroeconomic and 3 firm-specific variables to forecast news about the CF and DR components of investment growth.

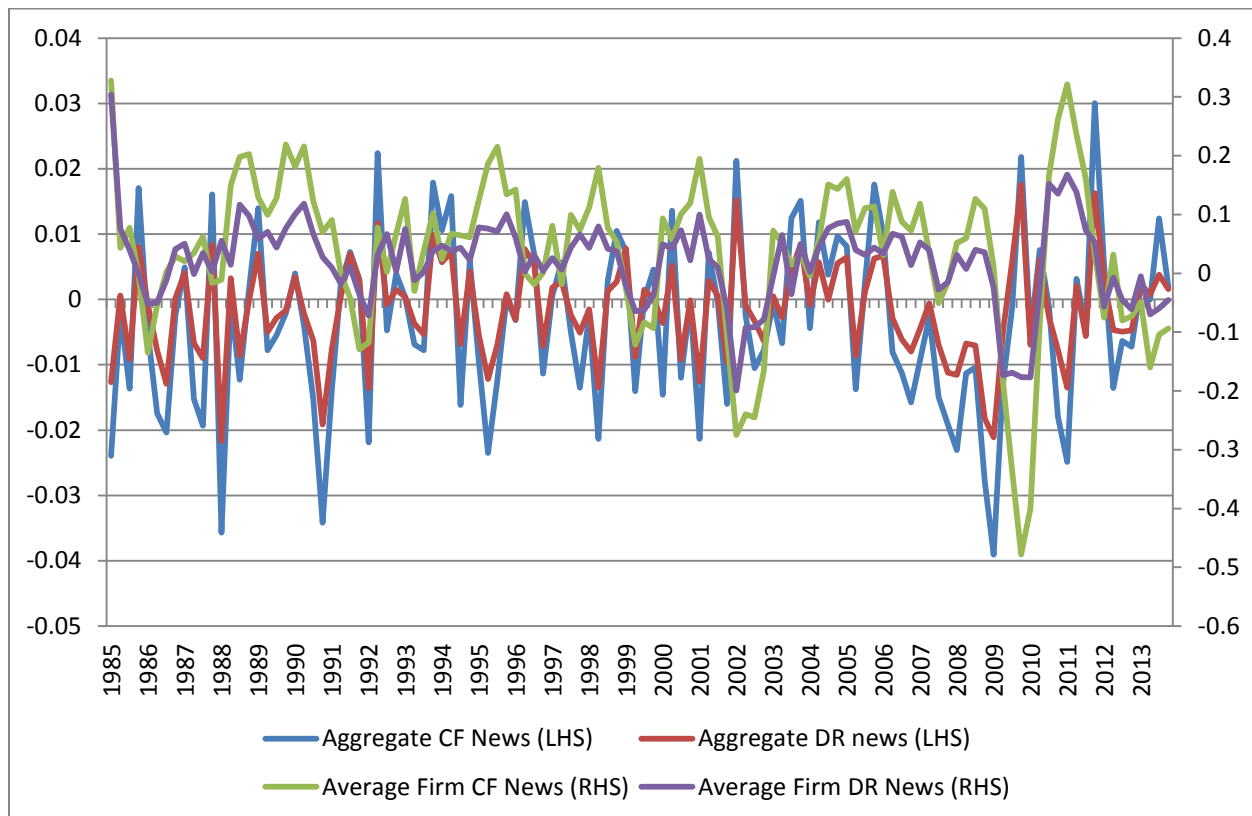


Figure 3: Average Values of Firm-level Growth Rates

This figure displays average quarterly values of firm-level investment growth rates and stock market returns. Asset growth (AG) is the average quarterly growth rate in total assets for sample firms. The investment growth rate (IG) is the average quarterly growth rate in capital expenditures for sample firms. Returns are the average quarterly stock returns for sample firms. Returns are measured by the right axis, while AG and IG are measured by the left axis.

