Estimation Risk, Information and the Conditional CAPM: Theory and Evidence[1]

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Abstract

We theoretically and empirically investigate the role of information on the cross-section of stock returns and firms' cost of capital when investors face estimation risk with respect to expected returns and learn from noisy signals of uncertain precision or quality. The resultant equilibrium is an endogenously derived conditional CAPM, where the market risk-premium, the market volatility, and the systematic estimation risk of stocks are information-dependent. Our empirical tests strongly support the predictions of the model. Market-wide and macroeconomic shocks that are correlated with shifts in market estimation risk — such as innovations in market volatility, oil prices, and the foreign exchange rate — not only carry a statistically significant price of risk, but their influence on individual stock returns depends on the stock's systematic estimation risk. Moreover, information-based and firm-specific factors such as innovations in the dispersion of analysts' forecasts help explain the cross-section of returns and carry a statistically significant price of risk, while an event study centered on dividend and share repurchase initiations reveals significant announcement effects on the estimated betas and their standard errors, in the direction predicted by the model.

Keywords: Estimation risk; Information quality; Conditional CAPM; Risk factors; Dividend initiations

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1 Introduction

How investors process new return related information and how this information affects equilibrium asset prices is a central issue in finance; it is of substantial interest not only to financial economists seeking to understand the informational efficiency of security prices, but also to investment practitioners who must make investment decisions in the face of continually arriving information. In the textbook capital asset pricing model (CAPM), which assumes that the investment opportunity set is common knowledge, prices simply adjust to new information so as to fall along the new security pricing line. However, this model of information absorption (in security markets) is not satisfactory from a variety of perspectives. Investment management professionals routinely prescribe investment advice and explain market movements in terms of 'resolution of uncertainty', which makes little sense in the standard CAPM.[1] Moreover, the asset pricing literature appears to be replete with results — both theoretical and empirical — that suggest a more complex and powerful interaction between information and equilibrium asset returns.

The assumption that investors have complete information regarding the return generating processes of assets is clearly extreme; in reality, investors are typically uncertain the parameters governing these processes, in addition to facing the risk that is intrinsic to production and investment. That is, investors also face estimation risk [e.g., Klein and Bawa (1976) and Barry and Brown (1985)]. But investors are also rarely *passive* about estimation risk; they use a variety of information sources — company announcements and disclosures, analyst reports, observed returns behavior and so on — to learn about the unknown parameters.

Often, however, investors are also uncertain about the *precision* or *quality* of these information sources. Take, for example, the case of newly public firms, where there is generally substantial estimation risk due to limited public information [e.g., Barry and Brown (1984) and Easley and O'Hara (2004)]. Here, investors are uncertain about both the information content of firms' financial policy choices and the reliability of analyst predictions. After all, if investors face estimation risk on the return generating processes of new firms, then it is difficult to see how they will be able to know the precision of arriving information. For example, there is evidence that investors are uncertain about the precision of analyst forecasts [Clement and Tse (2005)] and the interpretation

[1] Indeed, Wall Street economists often interpret market or stock movements in terms of investors waiting to be *convinced* about the pricing of various risk factors [see, e.g., McKay (2006)]. Of course, this is meaningless under the standard informational assumptions: At each instant in time, investors know exactly what risk factors to price and by exactly how much.

of financial disclosures by firms [Bailey et al. (2005)].

In this paper, we theoretically and empirically analyze the effects of estimation risk on the cross-section of stock returns and firms' cost of equity when investors learn from information of *uncertain* quality. To facilitate comparability with the standard CAPM, we construct a model where returns are multi-variate normal, but investors are uncertain about the first *and* second moments of the joint distribution of returns and signals. A crucial implication of learning from information of uncertain quality is that *both* the first and second conditional moments of expected returns are information-dependent, and hence stochastic. In equilibrium, assets are priced according to their systematic intrinsic risk *and* their systematic estimation risk. Moreover, the market risk-premium and volatility are information-dependent.

We therefore arrive *endogenously* at a *conditional* CAPM where the market risk-premium, the market volatility, and the systematic risk of individual assets are all sensitive to information that affects the market's conditional covariance of expected returns. The model is empirically rich, because it predicts that the cross-section of expected returns will *change* in response to new information that affects the priced estimation risk of assets. Specifically, changes in the market estimation risk will have a greater influence on stocks with higher systematic estimation risk , ceteris paribus. Further, the cost of capital of individual stocks will change as information emerges to alter the systematic estimation risk of the firm.

Our theoretical model implies that innovations in the market estimation risk-premium are positively correlated with innovations in market volatility. Thus, we predict that market volatility innovations will be a priced risk factor in the cross-section of stock returns. Moreover, the associated factor loadings of individual stocks will be positively correlated with their own systematic estimation risk. Our empirical tests support this prediction: we find that innovations in market volatility and their interactions with proxies for the systematic estimation risk of stocks — such as the firm's (public listing) age, the book-to-market, earnings-to-price, and dividend-to-price ratios — explain the cross-section of average returns in the direction predicted by the theory. For example, a 1% increase in market volatility decreases the average contemporaneous excess returns by over 4%, even when controlling for the usual risk factors, consistent with an increase in the cost of equity of the typical stock. However, other things held fixed, a 1% increase in the logarithm of the firm's (publicly listed) age *reduces* the price of volatility risk by over 1%.

Economic intuition suggests that the variation in the aggregate estimation risk will also be driven by innovations in macroeconomic variables that affect the probability distribution of cash flows of a cross-section of firms; one example is changes in prices of factor inputs, such as oil, that are significant earnings drivers for firms in a variety of industries; another example is changes in the foreign exchange rate that impact the cash flow prospects of firms that intensively use imported goods or have a significant export component in their earnings. Using a carefully constructed empirical test design, we find that *innovations* in oil prices and exchange rates have the predicted effects on stock returns. For example, innovations in oil prices carry a significant price of risk among the class of oil consuming firms. And, as predicted by the model, the effect of such innovations is exacerbated (ameliorated) for younger (older) firms, ceteris paribus.

However, macroeconomic or market-level innovations are not the only events that influence the estimation-risk-based risk-premia of firms. Our Bayesian-learning model predicts that equilibrium expected returns for stocks will be higher in not only more volatile market environments, but also when there is greater volatility in *firm-specific* information. Using the dispersion of analyst forecasts as a proxy for information uncertainty at the firm-level, we find that *innovations* in the dispersion of analyst forecasts help explain the cross-section of average returns, in the direction predicted by the model, even after controlling for the usual risk factors.

Our framework also implies that corporate events that affect the stock's estimation risk will have pricing effects because the new information influences the cost of equity. Our empirical analysis, based on the initiation of dividends (during 1963-2004) and share repurchases (during 1988-2004) supports these predictions. These watershed events in a firm's life-cycle plausibly reflect reduced uncertainty on cash flow risk [Lintner (1956) and Grullon et al. (2001)]. We find that the average estimated betas and their standard errors both decline (in a statistically significant fashion) immediately following the initiation events.

Our theoretical model and the empirical results — with respect to the cross-section of expected stock returns and information-based dynamics on the firms' cost of capital — are relevant to a number of streams of research in theoretical and empirical finance. Our research adds significantly to the literature on estimation risk. The role of estimation risk in asset pricing has long intrigued financial economists.[2] While early work conjectured that estimation risk would be "diversified away," Barry and Brown (1985) show that estimation risk can affect equilibrium returns if investors

[2] A very partial list of studies this area includes Zellner and Chetty (1965), Klein and Bawa (1976), Bawa et al. (1979), Barry and Brown (1984, 1985), Coles and Lowenstein (1988), Clarkson and Thompson (1990), Handa and Linn (1993), Kandel and Stambaugh (1996), Brennan and Xia (2001) and Xia (2001).

have heterogeneous beliefs, *assuming* that the CAPM holds. Empirically, researchers have noted that there is an age 'premium' in the cross-section of average returns [Barry and Brown (1984)] and that estimated betas tend to decline with age [Clarkson and Thompson (1990)]. By constructing an estimation risk based conditional CAPM when investors are uncertain about the higher moments of the distribution of returns and signals, we find support for the prediction that *macroeconomic-* or *market*-level variables will influence the cross-section of returns because of stocks' differential sensitivity to aggregate estimation risk.[3] Moreover, we identify proxies for the systematic estimation risk of individual stocks, such as *innovations* in the dispersion of analyst forecasts, that have heretofore not been explored in the literature. We also contribute to the literature on dividend initiations, that has largely interpreted announcement effects through the lens of altered cash flow expectations [e.g., Healy and Palepu (1988)], by providing evidence that this important event also affects the stock's required rate of return by influencing its systematic estimation risk.

The impact of oil price innovations on the cross-section of stock returns appears not to have been substantially discussed in the literature. But the relationship between market volatility and stock returns is extensively studied in the literature [see, Bekaert and Wu (2000)]. This literature typically explains the observed negative correlation between returns and market volatility through the leverage hypothesis [e.g., Black (1976) and Christie (1982)] or the time-varying risk-premium hypothesis [e.g., French et al. (1987)].[4] However, both the leverage and the time-varying risk premium explanations enjoy only partial empirical success [Wu (2001)]. Similarly, Vassalou (2000), building on the models of Solnik (1974), Grauer et al. (1976) and Adler and Dumas (1983), finds that exchange rate risk factors can help explain the within-country cross-sectional variation in average returns. Our framework not only suggests a novel reason for the pricing effects of *innovations* in market volatility and exchange rates, but also imposes additional restrictions — for instance, that the effect of these innovations on a stock will depend on its systematic estimation risk — that differentiate our model from the other hypotheses in the literature.

In a related vein, our theoretical and empirical results complement a recent literature that emphasizes information-based risk factors in asset pricing. Veronesi (2000) argues that equilibrium

[3] We note that while researchers have linked time-varying market risk-premium to estimation risk [e.g., Turner et al. (1989) and Mayfield (2004)], we theoretically and empirically explicate the influence of the aggregate estimation-risk on the cross-section of expected returns of stocks.

[4] The leverage effect hypothesis posits that a drop in the stock price (i.e., a reduced contemporaneous return) increases leverage and makes the stock more volatile, while the time-varying risk-premium perspective [e.g., French et al. (1987)] argues that an anticipated increase in volatility increases the required rate of return.

asset returns are quite sensitive to the specified precision of signals, while Easley and O'Hara [2004] develop the argument that firms' cost of capital is influenced by the ratio of public to private information. And, Easley et al. (2002) find empirical support for this prediction using a structural microstructure model. Our theoretical and empirical results complement these studies because information quality or precision is positively correlated with the ratio of public to private information. In fact, we contribute by providing evidence for information-based macroeconomic and firm-level risk factors not earlier explored in the literature.[5]

The conditional CAPM has attracted much attention in the recent literature as evidence accumulates that market betas along with the market risk-premium and volatility are time varying, and as researchers seek to explain the size and B/M based risk factors [Fama and French (1992, 1993)].[6] However, Wang (2003, page 162) observes that, "While this trade-off between time-varying risk and expected returns makes such [conditional] models intuitively appealing, it is empirically challenging, since there is no theoretical guidance on how betas and risk-premia vary with variables that represent conditioning information." This 'specification issue' is also emphasized by Harvey (1996), Ghysels (1998) and Brandt (1999).

Indeed, we find that a conditional CAPM derived from a primitive specification of asset returns and information structure is a useful source of empirical predictions that yield new empirical results and shed a different light on existing results. However, we present a different *approach* to testing the conditional asset pricing model, because our tests are quite distinct from the recent tests of the conditional CAPM. This literature focuses on introducing new risk-factors to improve the explanatory power of the model with respect to the cross-section of returns — often by showing improved cross-section R^2. But Lewellen et al. (2006) suggest caution in associating improved R^2 with superior empirical performance. Instead, we test refutable predictions on the *response* of the cross-section of returns and firm-specific betas to estimation risk related information. Thus, we provide an alternative way to specify the tests originating from the conditional CAPM, and in so doing develop results that contribute to a variety of empirical literatures.

In the remaining paper, Section 2 describes the basic model and derives the conditional CAPM. Section 3 develops the empirical implications of the model. Section 4 specifies the test design and presents the results of the empirical tests. Section 5 summarizes and concludes.

[5] On the other hand, unlike Easley and O'Hara (2004), we do not allow for differential information among investors, and hence there is no role for private information in our model.

[6] See Wang (2003) for a list of references reporting evidence of time-varying market betas, market risk-premium and market volatility. Lewell et al. (2006) provide a list of references proposing new risk factors.

2 Estimation Risk and the Conditional CAPM

2.1 Returns and Investor Preferences

We consider a canonical "single-period" economy with J perfectly divisible risky assets, where J is a large number. Asset rates of return, $\boldsymbol{r} = (r_1, ...r_J)'$, are multi-variate normal, with a mean vector $\boldsymbol{\mu} = (\mu_1, ...\mu_J)$ and the covariance matrix $\boldsymbol{\Sigma} = [\sigma_{ij}]$. There is also a riskless asset, the "$(J+1)$st" asset, with a known rate of return r_f. All assets are traded in competitive markets without transactions costs and taxes.

There are Z investors, $z = 1, ..., Z$, who each maximize the expected utility of the end-of-period-wealth and exhibit constant absolute risk-aversion; i.e., investor z's von-Neumann-Morgenstern expected utility function is, $U^z(W^z) = -\exp(-\phi^z W^z)$, $\phi^z > 0$.[7] Investors' investable wealth is denoted by $\bar{W}^z$, $z = 1, \ldots, Z$. Letting, $\boldsymbol{x}^z = (x_1^z, ...x_J^z)'$, denote the vector of portfolio weight of risky assets for investor z, the random end-of-the-period wealth is given by, $W^z = \bar{W}^z \left[1 + r_f + \boldsymbol{x}^{z\prime}(\boldsymbol{r} - \boldsymbol{r}_f)\right]$, where $\boldsymbol{r}_f = (r_f \cdot \mathbf{1})$ and $\mathbf{1}$ is the $J \times 1$ unit vector.

2.2 Estimation risk and Learning

We assume that investors do not know the mean return vector $\boldsymbol{\mu}$. (However, $\boldsymbol{\Sigma}$ is common knowledge.) Investors have homogenous prior beliefs about $\boldsymbol{\mu}$, and update on these beliefs based on *commonly observed signals* that are informative with respect to $\boldsymbol{\mu}$.[8] Specifically, all investors receive n signal vectors, $\boldsymbol{S} = (\boldsymbol{s}_1, \ldots, \boldsymbol{s}_n)$, $\boldsymbol{s}_t = (s_{1t}, \ldots, s_{Jt})$, $1 \le t \le n$, where the individual signals are generated by information innovations according to,

$$s_{it} = \mu_i + \epsilon_{it}, \qquad i = 1, \ldots, J; \qquad t = 1, \ldots, n. \tag{1}$$

[7] Constant absolute risk-aversion is not necessary for the conditional CAPM we derive below. However, the exponential expected utility function allows the investors' portfolio optimization to be multiplicatively separable in estimation and intrinsic risk.

[8] These signals are presumably received through accounting based disclosures such as earning announcements [e.g., Aharony and Swary (1980)], financial policy choices such as dividend initiations or shares repurchase decisions [e.g., Pettit (1972), Vermalaen (1981) and Asquith and Mullins (1983)], and mergers and acquisitions related developments [e.g., Loughran and Vijh (1997)]. The signals could also be received from outsiders, such as analysts, whose recommendation or projections can sometimes be informative [e.g., Brav and Lehavy (2003) and Sorescu and Subrahmanyam (2006)]. Finally, these signals could be based on macro- or market-level events that influence expected returns — for example, monetary, technological, and commodity supply shocks.

For each security i, the information innovations ϵ_{it} are i.i.d. normally distributed with mean zero and precision γ_{ii}.

Economic intuition suggests that the information innovations (ϵ_{it}) will be correlated across assets. Take, for example, the case where the signals belong to firms in the same industry grouping; or are being generated by analysts applying the same methodology across assets; or are derived from a common macroeconomic innovation. The correlation matrix of the information innovations is given by the (positive-definite) precision matrix $\mathbf{\Gamma} = [\gamma_{ij}]$. The likelihood function $f(\boldsymbol{S}\big|\boldsymbol{\mu}, \mathbf{\Gamma})$ is thus multivariate normal with mean vector $\boldsymbol{\mu}$ and the precision matrix $\mathbf{\Gamma}$.

For the reasons mentioned at the outset, we assume that investors are uncertain about $\mathbf{\Gamma}$. Moreover, investors' prior beliefs on the joint distribution of $(\boldsymbol{\mu}, \mathbf{\Gamma})$ belong to the Normal-Wishart family, i.e., there exists a vector $\boldsymbol{\nu}_0 = (\nu_{0,1}, \ldots, \nu_{0,J})$; a symmetric and positive-definite matrix, $\boldsymbol{\theta}_0 = [\theta_{0,ij}]$; and, scalars y and α such that the prior beliefs are, $q(\boldsymbol{\mu}, \mathbf{\Gamma}) = N_J(\boldsymbol{\mu}\big|\boldsymbol{\nu}_0, y\mathbf{\Gamma})\,\boldsymbol{Wi}_J(\mathbf{\Gamma}\big|\alpha, \boldsymbol{\theta})$, where $N_J(\boldsymbol{\mu}\big|\,\boldsymbol{\nu}_0, y\mathbf{\Gamma})$ is the $J-$dimensional multi-variate normal distribution with the mean vector $\boldsymbol{\nu}_0$ and precision matrix $y\mathbf{\Gamma}$. Meanwhile, $\boldsymbol{Wi}_J(\mathbf{\Gamma}\big|\,\alpha, \boldsymbol{\theta})$ is the $J-$dimensional Wishart distribution with the parameters α and $\boldsymbol{\theta}_0$, so that $E(\mathbf{\Gamma}\big|\alpha, \boldsymbol{\theta}_0) = \alpha\,(\boldsymbol{\theta}_0)^{-1}$.

2.3 Conditional Moments

The inference process for the annunciated system of prior beliefs and likelihood function is [see, e.g., Bernardo and Smith (1994, page 541)]:

Proposition 1 *Let $\boldsymbol{S}$ be a signal with the mean vector $\bar{\boldsymbol{s}} = (n)^{-1}\sum_{t=1}^{n}\boldsymbol{s}_t$ and the covariance matrix $\boldsymbol{D} = (n)^{-1}\sum_{t=1}^{n}(\boldsymbol{s}_t - \bar{\boldsymbol{s}})(\boldsymbol{s}_t - \bar{\boldsymbol{s}})'$. Put,*

$$\boldsymbol{\nu}(\boldsymbol{S}) = \frac{y\boldsymbol{\nu}_0 + n\bar{\boldsymbol{s}}}{y+n}; \quad \boldsymbol{\theta}(\boldsymbol{S}) = \boldsymbol{\theta}_0 + \frac{1}{2}\boldsymbol{D} + \frac{1}{2}\frac{ny(\boldsymbol{\nu}_0 - \bar{s})(\boldsymbol{\nu}_0 - \bar{s})'}{y+n}; \quad \alpha_n = \alpha + \frac{n}{2}. \tag{2}$$

Then, the marginal posterior beliefs of $(\boldsymbol{\mu}, \mathbf{\Gamma})$ are:

$$q(\boldsymbol{\mu}\big|\boldsymbol{S}) = \boldsymbol{t}_K(\boldsymbol{\mu}\big|\boldsymbol{\nu}(\boldsymbol{S}), (y+n)\alpha_n(\boldsymbol{\theta}(\boldsymbol{S}))^{-1}, 2\alpha_n) \quad \& \quad q(\mathbf{\Gamma}\big|\boldsymbol{S}) = \boldsymbol{Wi}_K(\mathbf{\Gamma}\big|\alpha_n, \boldsymbol{\theta}(\boldsymbol{S})), \tag{3}$$

where, $\boldsymbol{t}_K$ is the $K-$dimensional multivariate (Student's) $t-$distribution.

The multivariate $t-$distribution belongs to the family of elliptical distributions (E-D) [see, Owen and Rabinovitch (1983) and Fang et al. (1990)]. Hence, the posterior beliefs on $\boldsymbol{\mu}$ also belong to the E-D family, and this substantially aids tractability.

Proposition 1 shows that information innovations influence investors' posterior beliefs through their effect on the (signal) mean vector $\bar{\boldsymbol{s}}$ and the covariance matrix $\boldsymbol{D}$. In particular, the conditional mean and covariance matrix of $\boldsymbol{\mu}$ are, $E(\boldsymbol{\mu}|\boldsymbol{S}) = \boldsymbol{\nu}(\boldsymbol{S})$ and $\boldsymbol{\Psi}(\boldsymbol{\mu}|\boldsymbol{S}) = \boldsymbol{\theta}(\boldsymbol{S})[(2\alpha_n - 2)(y+n)]^{-1}$, respectively. Both the first and the second conditional moments are therefore random, and depend on the (realization of) the information history.

2.4 Learning and Portfolio Optimization

The fact that the posterior beliefs on the unknown expected returns ($\boldsymbol{\mu}$) belong to the E-D family is convenient, because if random variables are jointly elliptically distributed, then risk orderings from the expected utility criterion are identical to those derived from the more convenient mean-variance criterion [Chamberlain (1983) and Meyer (1987)]. Therefore, the investors' posterior portfolio optimization problem can be expressed in terms of the conditional expected returns and two types of risk: intrinsic return risk, represented by $\boldsymbol{\Sigma}$, and estimation risk represented by $\boldsymbol{\Psi}(\boldsymbol{S})$. Conveniently, under constant absolute risk-aversion, these risks are multiplicatively separable.

Take any investor $z = 1, ..., Z$. Using iterated expectations, we can write this investor's conditional expected utility as, $EU^z\left(W^z\middle|\boldsymbol{S}\right) = E_{\boldsymbol{\mu}}\left[-\exp(-\phi^z W^z|\boldsymbol{\mu})\middle|\boldsymbol{S}\right]$. Then, fix any risky asset portfolio, $\boldsymbol{x}^z$, and note that, *conditional* on $\boldsymbol{\mu}$, W^z is normally distributed. And using the moment-generating function for the multivariate normal distribution and the properties of the exponential function, we can write the investor's conditional expected utility function as,

$$E_{\boldsymbol{\mu}}\left[-\exp\left(-\phi^z\bar{W}^z[1+r_f+\boldsymbol{x}^{z\prime}(\boldsymbol{\mu}-\boldsymbol{r}_f)-\frac{\phi^z}{2}\bar{W}^z\boldsymbol{x}^{z\prime}\boldsymbol{\Sigma}\boldsymbol{x}^z]\right)\middle|\,\boldsymbol{S}\right] =$$
$$-\exp\left(-\phi^z\bar{W}^z[1+r_f-\frac{\phi^z}{2}\bar{W}^z\boldsymbol{x}^{z\prime}\boldsymbol{\Sigma}\boldsymbol{x}^z]\right)E_{\boldsymbol{\mu}}\left[\exp\left(-\phi^z\bar{W}^z\boldsymbol{x}^{z\prime}(\boldsymbol{\mu}-\boldsymbol{r}_f)\right)\middle|\,\boldsymbol{S}\right] \qquad (4)$$

Now, put $w^z \equiv \bar{W}^z\boldsymbol{x}^{z\prime}(\boldsymbol{\mu}-\boldsymbol{r}_f)$; i.e., w^z is the *expected* dollar return on the risky assets earned in excess of the risk-free return. But the distribution of w^z belongs to the E-D family since $(\mu_1, \ldots, \mu_J)$ have the multivariate $t-$distribution and linear combinations of these variables also have the $t-$distribution [see, e.g., Owen and Rabinovitch (1983)]. And since the CARA expected utility function is a strictly increasing and concave utility function, it follows that there exists a mean-variance representation of estimation-risk component of (4). To express this concisely, note that, conditional on the signals $\boldsymbol{S}$, the first two conditional moments of w^z are, $E(w^z|\boldsymbol{S}) \equiv \bar{W}^z[\boldsymbol{x}^{z\prime}(\boldsymbol{\nu}(\boldsymbol{S})-\boldsymbol{r}_f)]$ and $\Delta(w^z|\boldsymbol{S}) \equiv (\bar{W}^z)^2\boldsymbol{x}^{z\prime}\boldsymbol{\Psi}(\boldsymbol{S})\boldsymbol{x}^z$, where, $\boldsymbol{\Psi}(\boldsymbol{S}) = [\psi_{ij}(\boldsymbol{S})]$ is the conditional covariance matrix of $\boldsymbol{\mu}$.

Then,

$$EU^z\left(W^z\big|\boldsymbol{S}\right) = -\exp\left(-\phi^z\bar{W}^z[1+r_f - \frac{\phi^z\bar{W}^z}{2}\boldsymbol{x}^{z\prime}\boldsymbol{\Sigma}\boldsymbol{x}^z]\right)G^z\left(E(w^z\big|\mathbf{S}), \Delta(w^z\big|\boldsymbol{S})\right), \tag{5}$$

where, $-G^z$ is the mean-variance representation of the part of the investors' expected utility function that is subject to estimation risk. Because any risk-averse expected utility function is increasing in the mean and decreasing in variance of random variables drawn from the E-D family [e.g., Meyer (1987)], G^z is therefore decreasing in the first conditional moment and increasing in the second conditional moment of the dollar excess returns. For future reference, we let $Y_j^z(\boldsymbol{S}, \boldsymbol{x}^z) \equiv -(G_j^z/G^z)$, where G_j^z denotes the derivative of G^z with respect to the j^{th} argument. Thus, $Y_1^z > 0$ and $Y_2^z < 0$.

2.5 Equilibrium Conditional Risk-Premia

Investors have conditional mean-variance expected-utility functions, because the posterior beliefs on the unknown mean returns are elliptically distributed. We therefore know from Chamberlain (1983) that in equilibrium the risk-premia of assets, conditional on the signals ($\mathbf{S}$), will be a linear function of the (conditional) market risk- premium. However, the assets' loading on the market risk-premium, i.e., their systematic risk, will be influenced by the estimation risk.

To facilitate intuition on the empirical content of estimation risk, we illustrate how the conditional second moments of the expected returns (i.e., $\boldsymbol{\Psi}(\boldsymbol{S})$) influence the systematic risk for the case of two risky assets ($j = 1, 2$). Consider the welfare effects of a small portfolio rebalancing from the risk-less asset toward, say, asset 1, for the typical investor (z). This adjustment increases portfolio risk on two accounts: first, it increases portfolio return risk; in addition, it increases the investor's exposure to estimation risk. In terms of marginal expected utility, the total increase in risk exposure is proportional to,

$$\sigma_{11} + \sigma_{12} - Y_2^z(\boldsymbol{S}, \boldsymbol{x})[\psi_{11}(\boldsymbol{S}) + \psi_{12}(\boldsymbol{S})], \tag{6}$$

where, $\psi_{ij}(\boldsymbol{S}) = \text{Cov}(\mu_i, \mu_j\big|\mathbf{S})$, $i, j = 1, 2$. In the absence of estimation risk, only the intrinsic risk components, i.e., σ_{11} and σ_{12}, will be relevant. The last term in (6) reflects the investor's systematic estimation risk for asset 1, i.e., the increase in the *portfolio* estimation risk, at the margin, from increasing investment in the asset.

We now express the equilibrium conditional risk-premia, $\boldsymbol{\nu}(\boldsymbol{S}) - \boldsymbol{r}_f$, in terms of the assets' contribution to the *augmented risk* of the market portfolio, denoted by $\boldsymbol{x}^M(\mathbf{S})$. Because of the presence of estimation risk, holding the market portfolio imposes two types of risk on investors: *intrinsic risk,* given by the covariance matrix $\boldsymbol{\Sigma}$, and *estimation risk,* given by $\boldsymbol{\Psi}(\boldsymbol{S})$, which represents the market's conditional beliefs on the second moments of the unknown mean returns ($\boldsymbol{\mu}$). The conditional market risk-premium, i.e., $R_M(\boldsymbol{S}) \equiv \boldsymbol{x}^M(\mathbf{S})' \ (\boldsymbol{\nu}(\boldsymbol{S}) - \boldsymbol{r}_f)$, therefore, reflects compensation for facing both these risks.

Consequently, the priced risk of assets also must have two components, namely, their contribution to the intrinsic and estimation risk of the market portfolio. So imagine that in holding the market portfolio, investors hold two risky portfolios, say $\bar{M}$ and $\tilde{M}$, each with the portfolio weight vector $\boldsymbol{x}^M(\mathbf{S})$, and conditional returns $r_{\bar{M}}(\mathbf{S})$ and $r_{\tilde{M}}(\mathbf{S})$, respectively. We interpret $\tilde{M}$ as a portfolio whose risk, conditional on signals $\mathbf{S}$, is represented by, $\boldsymbol{\Psi}(\boldsymbol{S})$. Then, the contribution of asset j to the intrinsic risk of the market portfolio is, $\text{Cov}(r_{\bar{M}}(\mathbf{S}), r_j) = \sum_{i=1}^{J} x_i^M(\mathbf{S})\sigma_{ij}$. Its contribution to the estimation risk of the market portfolio is, $\text{Cov}(r_{\tilde{M}}(\mathbf{S}), r_j) = \sum_{i=1}^{J} x_i^M(\mathbf{S})\psi_{ij}(\boldsymbol{S})$.

A basic feature of the standard CAPM is that the equilibrium risk-premia of assets are proportional to their covariance with the market return. Based on the foregoing, the equilibrium risk-premia of assets in the presence of estimation risk should be a weighted average of their contribution to the intrinsic and estimation risk of the market portfolio, i.e., $r_{\bar{M}}(\mathbf{S})$ and $r_{\tilde{M}}(\mathbf{S})$, respectively. This is indeed the case. Let, $\mathbf{C}_{\bar{M}} = (\text{Cov}(r_{\bar{M}}(\mathbf{S}), r_1), ..., \text{Cov}(r_{\bar{M}}(\mathbf{S}), r_J))'$ and $\mathbf{C}_{\tilde{M}}(\boldsymbol{S}) = \left(\text{Cov}(r_{\tilde{M}}(\mathbf{S}), r_1), ..., \text{Cov}(r_{\tilde{M}}(\mathbf{S}), r_J)\right)'$. Then, in equilibrium, there exist positive scalars $L_{\bar{M}}(\boldsymbol{S})$ and $L_{\tilde{M}}(\boldsymbol{S})$ such that,

$$\boldsymbol{\nu}(\boldsymbol{S}) - \boldsymbol{r}_f = L_{\bar{M}}(\boldsymbol{S})C_{\bar{M}} + L_{\tilde{M}}(\boldsymbol{S})C_{\tilde{M}}(\boldsymbol{S}), \tag{7}$$

Here, $L_{\bar{M}}$ and $L_{\tilde{M}}$ are proportional to the market's (aggregate) risk-tolerance with respect to intrinsic and estimation risk, respectively.[9]

It now remains to derive the conditional CAPM representation of equilibrium asset risk-premia. In the standard CAPM, market risk-premium is proportional to the risk of the market portfolio. A natural extension of this relationship in the presence of estimation risk is that market risk-premium is a linear combination of aggregate intrinsic and estimation risk. Indeed, by pre-multiplying both sides of (7) by $\boldsymbol{x}^{M\prime}$, we get,

$$R_M(\boldsymbol{S}) = L_{\bar{M}}(\boldsymbol{S})\sigma^2_{\bar{M}}(\mathbf{S}) + L_{\tilde{M}}(\boldsymbol{S})\sigma^2_{\tilde{M}}(\boldsymbol{S}) \tag{8}$$

[9]The derivation of equation (7) is straightforward; details are available upon request.

where, $\sigma^2_{\bar{M}}(\mathbf{S}) = \sum_i \sum_j x_i^M(\mathbf{S}) x_j^M(\mathbf{S}) \sigma_{ij}$ and $\sigma^2_{\tilde{M}}(\mathbf{S}) = \sum_i \sum_j x_i^M(\mathbf{S}) x_j^M(\mathbf{S}) \psi_{ij}(\boldsymbol{S})$. For notational ease, we put, $\sigma^2_M(\mathbf{S}) \equiv L_{\bar{M}}(\boldsymbol{S})\sigma^2_{\bar{M}}(\mathbf{S}) + L_{\tilde{M}}(\boldsymbol{S})\sigma^2_{\tilde{M}}(\boldsymbol{S})$. Then, substituting (8) in (7) yields,

Theorem 1 *In equilibrium, the asset risk-premia, conditional on the signal history* $\boldsymbol{S}$, *are given by:*

$$\begin{aligned} \boldsymbol{\nu}(\boldsymbol{S}) - \boldsymbol{r}_f &= \left[\frac{L_{\bar{M}}(\boldsymbol{S})C_{\bar{M}} + L_{\tilde{M}}(\boldsymbol{S})C_{\tilde{M}}(\boldsymbol{S})}{\sigma^2_M(\mathbf{S})}\right] R_M(\boldsymbol{S}) \\ &\equiv \left(\boldsymbol{\beta}^{IR}(\boldsymbol{S}) + \boldsymbol{\beta}^{ER}(\boldsymbol{S})\right) R_M(\boldsymbol{S}). \end{aligned} \tag{9}$$

In equilibrium, the conditional risk-premium of an asset — given the information history, $\boldsymbol{S}$ — can be decomposed into two components: the risk-premium due to the asset's *intrinsic* systematic risk, namely, $\boldsymbol{\beta}^{IR}(\boldsymbol{S})R_M(\boldsymbol{S})$; and, the risk-premium due to the asset's sensitivity to the market estimation risk factor, namely, $\boldsymbol{\beta}^{ER}(\boldsymbol{S})R_M(\boldsymbol{S})$. Moreover, both the market risk-premium (i.e., $R_M(\boldsymbol{S})$) and the market volatility (i.e., $\sigma^2_M(\mathbf{S})$) are *stochastic* and conditional on the signals. This is because the market risk-premium is composed of the compensation investors require for exposing themselves to the intrinsic market risk (determined by $\boldsymbol{\Sigma}$) and the estimation risk of the market portfolio (determined by $\boldsymbol{\Psi}(\boldsymbol{S})$). Hence, the market risk-premium and volatility will vary as the conditional second moments of the unknown mean returns evolve in response to changes in $\mathbf{S}$.

The assumption that investors are uncertain about the second moments of the distribution of returns and signals is important. If $\boldsymbol{\Gamma}$ is common knowledge, then the conditional second moments of the expected returns will be deterministic and a function of the signal sample size (n) alone [DeGroot (1970, page 175)].[10] The equilibrium asset risk-premia will therefore themselves be independent of the information, $\boldsymbol{S}$, and the augmented beta will converge to the standard beta deterministically as n gets large. By contrast, with uncertain conditional second moments, the systematic risk of assets will fluctuate with the information available to investors, a fact that we will exploit in our empirical tests below.

[10] More precisely, suppose that $\boldsymbol{\Gamma}$ is common knowledge and investors' prior on $\boldsymbol{\mu}$ is normal with mean $\boldsymbol{\nu}_0$ and precision matrix $\boldsymbol{\tau}$. Then, conditional on observing signals $\mathbf{S}$, the conditional precision matrix is, $(\boldsymbol{\tau} + n\boldsymbol{\Gamma})$, which is indepenedent of $\mathbf{S}$.

3 Empirical Implications

In this section, we develop the empirical implications of the conditional CAPM given in Theorem 1. In the succeeding sections, we develop the empirical tests of these implications, using a variety of empirical proxies — at both the firm- and the market-level — which we then test.

While we have set-up our model in a static framework for tractability and comparison with the standard CAPM, the (Bayesian) learning-based conditional CAPM derived above is empirically rich, because it predicts that the systematic risk of assets will be influenced by news or information innovations — at the market and firm level — that affect the conditional mean and covariance of returns. Specifically, the systematic risk of assets, and hence their equilibrium expected returns, can be affected by return-related news in either of two ways:

1. The estimation risk component of the market risk-premium (i.e., $R_M(\boldsymbol{S})$) can change; the effect on an asset's systematic risk then depends on its estimation risk beta (i.e., $\boldsymbol{\beta}^{ER}(\boldsymbol{S})$).
2. For a fixed market risk-premium, the estimation risk beta, $\boldsymbol{\beta}^{ER}(\boldsymbol{S})$, can itself change, thereby modifying the asset's overall priced risk.

Clearly, (1) will apply for macroeconomic or market-wide (information) events, while (2) will apply for firm-specific events. Specifically, in the context of equation (9), the first effect (1) changes the conditional risk-premia $(\boldsymbol{\nu}(\boldsymbol{S}) - \boldsymbol{r}_f)$ because of a change in $R_M(\boldsymbol{S})$, while the second effect (2) changes $(\boldsymbol{\nu}(\boldsymbol{S}) - \boldsymbol{r}_f)$ because of changes in $\boldsymbol{\beta}^{ER}(\boldsymbol{S})$. Thus, our model imposes restrictions on the effects of changes in the market estimation risk and the systematic estimation risk of individual stocks on the cross-section of returns and on the cost of equity.

3.1 Market Estimation Risk and the Cross-Section of Stock Returns

The definition of the estimation risk beta (β^{ER}) suggests that stocks whose estimation risk is more highly correlated with the estimation risk of the market-portfolio will exhibit greater changes in expected returns in periods when the aggregate estimation risk itself changes. This is because the estimation risk of such stocks is more sensitive to changes in the market-wide estimation risk. We now build on this insight to arrive at an empirically testable specification.

We start by expressing the conditional CAPM (cf. (9)) for any asset i in time-period t as,

$$E\left[r_{it}\middle|\mathbf{S}_t\right] = r_{ft} + \left(\beta_{it}^{IR} + \beta_{it}^{ER}\right) R_{Mt}, \tag{10}$$

where, $\mathbf{S}_t$ is the common signal or information set of investors at the beginning of time-period t, r_{ft} is the risk-free rate, $\beta_{it}^{IR} = \beta_i^{IR}(\mathbf{S}_t)$, $\beta_t^{ER} = \beta^{ER}(\mathbf{S}_t)$, and $R_{Mt} = R_M(\mathbf{S}_t)$. Integrating out the signals $\mathbf{S}_t$, and assuming that $\bar{r}_f = E[r_{ft}]$ exists, we can re-write (10) in its unconditional form as,

$$E[r_{it}] = \bar{r}_f + (\bar{\beta}_i^{IR} + \bar{\beta}_i^{ER})\bar{R}_M + \text{Cov}(R_{Mt}, \beta_{it}^{IR}) + \text{Cov}(R_{Mt}, \beta_{it}^{ER}), \tag{11}$$

where, $\bar{R}_M = E[R_{Mt}]$, $\bar{\beta}_i^{IR} = E\left[\beta_{it}^{IR}\right]$, and $\bar{\beta}_i^{ER} = E\left[\beta_{it}^{ER}\right]$.

The expected-return representation in (11) provides a convenient decomposition of the stock's systematic risk between its intrinsic and estimation risk components. Indeed, absent the last right-hand-side term, equation (11) has been well studied in the conditional CAPM literature [see, e.g., Jagannathan and Wang (1996)], because the regression estimate from the standard market model [Brown and Warner (1985)] is equal to, $\bar{\beta}_i \equiv (\bar{\beta}_i^{IR} + \bar{\beta}_i^{ER})$. However, because our focus is on providing empirical content to $\text{Cov}(R_{Mt}, \beta_{it}^{ER})$, for parsimony we will represent the first three right-hand-side terms of (11) by the market model.[11]

We interpret $\text{Cov}(R_{Mt}, \beta_{it}^{ER})$ as the sensitivity of the asset's estimation risk beta to innovations in the estimation risk component of the market risk-premium. In general, we would expect such sensitivity to depend on firm-specific characteristics; for example, the sensitivity will be higher for firms with greater *valuation uncertainty* due to difficulties in estimating the expected returns. To see this point, imagine the extreme situation where the expected return of an asset is perfectly known, so that their is no estimation risk. Clearly, in such a case, $\text{Cov}(R_{Mt}, \beta_{it}^{ER}) = 0$.

Then let, υ_t, be a macroeconomic or market-level variable that is positively correlated with the estimation risk component of the market risk-premium. We will consider the specification,

$$\text{Cov}(R_{Mt}, \beta_{it}^{ER}) = \sum_{k=1}^{K} \gamma_{ik}\xi_{ik,t} + \sum_{k=1}^{K} \lambda_{ik}(\upsilon_t - \bar{\upsilon})\xi_{ik,t} \tag{12}$$

Here, ξ_{ik}, $k = 1, ..., K$, are time-varying firm-specific characteristics that influence the systematic estimation risk of the firm. The mean value of the characteristics is normalized at zero, without loss of generality. Hence, (12) implies that the covariance of the asset's estimation risk beta with the market risk-premium at the beginning of time-period t, i.e., $\text{Cov}(R_{Mt}, \beta_{it}^{ER})$, is a linear function of the sample covariance of υ_t with a pre-specified set of firm characteristics (ξ_{ik}). The formulation

[11] Where appropriate — for example, where our analysis adds to empirical specifications already extant in the literature — we supplement market risk with the size and market-to-book factors [Fama-French (1992,1993)], along with the momentum factor.

is flexible enough to allow for time-variation in these characteristics.

The content of our model is then given by the prior restrictions on the signs of the coefficients γ_{ik} and λ_{ik}. For example, if higher values of ξ_{ik} increase the the asset's systematic estimation risk, then $\gamma_{ik} > 0$ and $\lambda_{ik} > 0$. Below, we will specialize υ_t to include market-level variables such as innovations in market volatility and macroeconomic variables such as oil price and exchange rate shocks. And we will identify the firm characteristics (ξ_{ik}) with the firm's age and with the earnings-to-price, book-to-market, and dividend-to-price ratios.

3.2 Information Spreads and the Cross-Section of Stock Returns

The fine structure of our Bayesian learning-based model imposes restrictions on the relationship between the cross-section of returns at any given time and observable characteristics of the *signal history* ($\boldsymbol{S}$) of assets up-to that point. Specifically, Proposition 1 implies that, for any asset i, the first two sample signal moments, i.e., $\bar{s}_i = (1/n)\sum_{\tau=1}^{n} s_{i\tau}$ and $\bar{s}_i^2 = (1/n)\sum_{\tau=1}^{n}(s_{i\tau} - \bar{s}_i)^2$ will influence the posterior mean and variance of the expected return (μ_i). It is easy to see that the posterior variance of μ_i is increasing in the sample variance ($\bar{s}_i^2$). We will say that the signal history $\mathbf{S}_i^* = (s_{i1}^*, ..., s_{i\tau}^*)$ second-order stochastically dominates the signal history $\mathbf{S}_i^{**} = (s_{i1}^{**}, ..., s_{i\tau}^{**})$ if $\bar{s}_i^{2**} > \bar{s}_i^{2*}$, but $\bar{s}_j^* = \bar{s}_j^{**}$ and $\bar{s}_{ij}^* = \bar{s}_{ij}^{**}$, $i \neq j$; that is, $\mathbf{S}_i^{**}$ is a spread on $\mathbf{S}_i^*$.

Intuitively, we expect that own signal spreads will increase the estimation risk premium on an asset, because they increase the posterior second moment (or uncertainty) regarding the unknown mean return. It is straightforward to establish,

Proposition 2 *For any security, $i = 1, ...J$, if S^* and S^{**} are such that S_i^* second-order stochastically dominates S_i^{**}, then $\beta_i^{ER}(S^{**}) > \beta_i^{ER}(S^*)$.*

Of course, signal variance *per se* has no role in the equilibrium risk-premia defined by the standard CAPM. Signal variance will also not influence equilibrium returns in models with estimation risk where the posterior second (or higher) moments are known or are not random.

Proposition 2 has implications for the effects on the cross-section of equilibrium returns of firm-specific information that increases the variance of signals. Let, $\omega_{it} \equiv (1/t)\sum_{\tau=1}^{t}(s_{i\tau} - \bar{s}_i)^2$, be the (sample) variance of the signals for firm i at the beginning of time-period t. Then, controlling for other risk factors, the expected return of the stock of firm i should be increasing in ω_{it}. In particular, if we take the expected return specification,

$$E[r_{it}] = \bar{r}_f + \bar{\beta}_i \bar{R}_M + \eta_i \omega_{it}, \tag{13}$$

then our model imposes the restriction that $\eta_i > 0$.

3.3 Announcement Effects on Firms' Cost of Capital

The learning-based conditional CAPM derived above also suggests announcement effects on the *cost of capital* of (individual) firms. Events that impact the stock's estimation risk components, namely, ψ_{ij}, will also affect the stock's market risk loading and therefore influence its equilibrium risk-premium. Unlike the usual event-study story that interprets announcement effects of corporate events through changes in expected cash flows of stocks, in our model the transmission mechanism for such announcement effects is changes in the market's estimate of the firm's cost of capital.

Consider a corporate event relating to some firm i, occurring at some date τ. We denote by $\boldsymbol{S}_{i,\tau-1}$ and $\boldsymbol{S}_{i,\tau+1}$ the signal histories immediately prior and posterior to the event, respectively. The event reduces estimation risk for stock i if: $\psi_{ii}(\boldsymbol{S}_{i,\tau+1}) < \psi_{ii}(\boldsymbol{S}_{i,\tau-1})$, $\psi_{ij}(\boldsymbol{S}_{i,\tau+1}) \leq \psi_{ij}(\boldsymbol{S}_{i,\tau-1})$, for each $i \neq j$, and $\psi_{jk}(\boldsymbol{S}_{i,\tau+1}) = \psi_{jk}(\boldsymbol{S}_{i,\tau-1})$, $j, k \neq i$. Therefore, firm-specific events that reduce the estimation risk for asset i also reduce their conditional estimation risk beta, i.e., $\beta_i^{ER}(\boldsymbol{S}_{i,\tau+1}) < \beta_i^{ER}(\boldsymbol{S}_{i,\tau-1})$.

Unlike the empirical implications of the estimation risk and learning based conditional CAPM derived above, the announcement effects (through firm-specific events) on the cost of capital are appropriately tested in an event study framework. Here, we use the fact that the betas estimated from the standard market model already incorporate the asset's priced estimation risk (cf. Theorem 1). Thus, immediately following an event that reduces the estimation risk beta, the stock's observed loading on the market factor will fall, and the announcement date abnormal returns will be positive.

So suppose that such an event occurs at date τ and we estimate the pre- and post-event market factor loadings for the stock by using the market model [see, e.g., Brown and Warner (1985)],

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t}, \tag{14}$$

for $t = \tau - T, \ldots, \tau$ and $t = \tau, \ldots, \tau + T$, respectively. Let the pre- and post-event estimated betas be denoted $\hat{\beta}_i(\boldsymbol{S}_i^-)$ and $\hat{\beta}_i(\boldsymbol{S}_i^+))$, respectively. Then the hypothesis is that $\hat{\beta}_i(\boldsymbol{S}_{i,\tau+1}) < \hat{\beta}_i(\boldsymbol{S}_i^-)$.

We can also derive some other refutable predictions by imposing further structure on the estimation risk effects of the corporate event. We note that conditional on the signal history, S_{it}, the disturbance terms ϵ_{it} in (14) are mean zero random variables. But, in general, the matrix of second-order moments, $V(\boldsymbol{S}_t) \equiv E[\epsilon_{i,t}\epsilon_{j,t-k} \big| \boldsymbol{S}_t]$ may be non-diagonal. We will let $\text{Var}_i(\boldsymbol{S}_t) = E[\epsilon_{i,t}^2 \big| \boldsymbol{S}_t]$, and denote by Std. Error$(\hat{\beta}_{i,t})$, the standard error of the beta estimate in the market model. Now, an estimation risk reducing event will also reduce the specification error in (14), because a part of the specification error arises from uncertainty regarding the parameters of the equilibrium return distribution. In this situation, the post-event standard errors of the beta estimates will be lower compared to their pre-event counterparts, i.e., Std. Error$(\hat{\beta}_i(\boldsymbol{S}_{i,\tau+1}))$ < Std. Error$(\hat{\beta}_i(\boldsymbol{S}_{i,\tau-1}))$.

4 Test Design and Results

In this section, we drive the empirical models developed in the previous section to the data by choosing empirical proxies for the estimation risk of the market and the systematic estimation risk of individual stocks. We then report and discuss the results of the empirical analysis.

4.1 Market Volatility Innovations and the Cross-section of Stock Returns

In (12), υ_t is a covariate that is highly correlated with the estimation risk component of the market risk-premium. But in our theoretical framework, the (time-varying) market volatility $\sigma_M^2(\mathbf{S}_t)$ is a natural candidate for υ_t. This is because, according to equation (8), the estimation risk component of the market risk-premium is highly correlated with market volatility. Thus, we can readily proxy υ_t by the market volatility, $\sigma_{Mt}^2 \equiv \sigma_M^2(\mathbf{S}_t)$.

In terms of the specification set out in (12), equation (8) in fact implies that the aggregate estimation risk — and therefore the market risk-premium — is positively related to *innovations* in market volatility. For example, in periods with unexpectedly high market volatility, stocks with the highest systematic estimation risk (i.e., β_{it}^{ER}), should exhibit the highest magnitude of increases in expected returns or, equivalently, declines in contemporaneous excess returns. To empirically implement (12), it then remains to specify the firm-specific characteristics, ξ_{ik}. Intuitively, characteristics that make it more difficult to reliably estimate the first and second moments of the expected return on the firm's equity will positively and significantly influence $\text{Cov}(R_{Mt}, \beta_{it}^{ER})$, and hence also the expected return (cf. (11)). With this interpretation, a variety of literatures in financial economics suggest suitable empirical proxies for these characteristics.

As we have mentioned before, there is considerable empirical evidence in the literature that younger firms typically are more susceptible to estimation risk [e.g., Clarkson and Thompson (1990)]. This is also plausible from introspection since investors typically have the least amount of data to reliably estimate the parameters of the return distribution for such firms. In fact, Barry and Brown (1984) find that cross-sectionally older firms earn less expected excess returns, ceteris paribus. But our model goes further and predicts that the pricing effects of market volatility innovations will be exacerbated (or ameliorated) for older (or younger) firms.

Specifically, for each firm, i, we let $\delta(\sigma^2_{Mt}) = \sigma^2_{M,t} - \sigma^2_{M,t-1}$, be the innovation in the market volatility between the beginning of time-period $t-1$ and t. We then specialize (12) as:

$$r_{it} - r_{ft} = \alpha_i + \pi_i \delta(\sigma^2_{Mt}) + \gamma_i \text{ age}_{it} + \lambda_i[\delta(\sigma^2_{Mt}) * \text{age}_{it}] + \beta_i(r_{Mt} - r_{ft}), \tag{15}$$

where, r_{it} is the monthly rate of return for firm i during month t (or "at" time t), r_{ft} is the rate of return on a one-month Treasury bill at time t, r_{Mt} is the value-weighted return of the stock market at time t, and age_{it} is the natural logarithm of firm's i age at time t, measured as the number of months the firm has been listed on CRSP. We note that r_{it} is the rate of return for firm i at time t *contemporaneous* to the volatility innovations. Therefore, the model imposes the following restrictions on (15):

Hypothesis 1 *In the regression equation (15),* $\pi_i < 0$*,* $\gamma_i < 0$*, and* $\lambda_i > 0$.

More generally, the systematic estimation risk of stocks will be high in those environments where it is more difficult to reliably assess the probability distribution of returns, so that the conditional mean and variance of returns is especially sensitive to new information. In terms of the widely-used decomposition of equity values into assets-in-place and growth options [see, Myers (1977)], it is intuitively clear that the systematic estimation risk would be positively correlated with the proportion of equity value explained by growth options; in the extreme case where all value resides in perfectly known assets-in-place, there is no estimation risk. Thus, firm characteristics that are positively correlated with the portion of equity value in growth options — such as high P/E and market-to-book ratios, and low dividend yield (D/P) — will also exhibit higher systematic estimation risk or greater sensitivity to variations in aggregate estimation risk.

We test the effects of innovations in market volatility on the cross-section of returns by examining the firm-specific stock price responses to such innovations in terms of the just annunciated firm characteristics. Returning to (12), we set $K = 3$, with $\xi_{i1,t} = \text{B/M}_{it}$, $\xi_{i2,t} = \text{E/P}_{it}$, and $\xi_{i3,t} = \text{D/P}_{it}$, where these are the book-to-market, earnings-to-price, and the dividend-to-price ratios, respectively, for firm i at the beginning of time-period t. Specifically, for each firm, i, we first estimate the regression:

$$r_{it} - r_{ft} = \alpha_i + \pi_i \delta(\sigma^2_{Mt}) + \beta_i(r_{Mt} - r_{ft}) \tag{16}$$

We then sort firms into quintiles according to each characteristic, $\xi_{ik,t}, k = 1, 2, 3$, and compute the average coefficient, $\hat{\pi}_y$, $y = 1, 2, ...5$, in each quintile group.[12] The refutable prediction from our model is then that,

Hypothesis 2 $\hat{\pi}_y < 0$, $y = 1, 2, ...5$, *and moreover,* $\hat{\pi}_1 < \hat{\pi}_2 < ...\hat{\pi}_5$.

4.1.1 Data and Results

Using the daily value-weighted market index from CRSP for the period 1964-2005, we compute the market volatility *innovation* in month t, i.e., $\delta(\sigma^2_{Mt}) = \sigma^2_{M,t} - \sigma^2_{M,t-1}$, where, $\sigma^2_{M,t} = \sqrt{\sum_{q=1}^{Q-1} (r_{M,t+q+1} - r_{M,t+q})^2 / Q}$ and $r_{M,t+q}$ is the daily return on the market portfolio on day q of month t, with Q representing the number of trading days in the month [see, Moise(2006)].[13] We estimate equation (15) for each stock available on the CRSP database during the period 1964-2004. We impose the constraint that each stock have at least 12 months of return data available, which results in a total sample size of 22,081 stocks (throughout the sample period).

Table 1 presents the tests for Hypothesis 1, and reports cross-sectional averages of firm-specific coefficients π_i, γ_i, and λ_i, in regression equation (15). We also report *t-statistics* computed in the cross-section. For robustness, we estimate an alternative specification using an augmented version of equation (15) that includes the SMB and HML factors of Fama and French (1992, 1993):

$$r_{it} - r_{ft} = \alpha_i + \pi_i \delta(\sigma^2_{Mt}) + \gamma_i \text{ age}_{it} + \lambda_i[\delta(\sigma^2_{Mt}) * \text{age}_{it}] + \beta_i(r_{Mt} - r_{ft}) + s_i \text{ SMB}_t + h_i \text{ HML}_t, \tag{17}$$

where, SMB_t is the difference in returns between portfolios of large stocks and portfolios of small stocks, and HML_t is the difference in returns between portfolios of stocks with high and low book-to-market ratios.

[12] We obviously do not include the M/B and Size factors in the regression specification (16) because the sorting characteristics include these variables. And the interaction term is redundant because it is implicitly captured in the variation of the $\bar{\pi}_y$ across the quintiles.

[13] For robustness we repeat the tests with volatility measured from the equally-weighted market index and the results are qualitatively similar.

We also use a four-factor model that includes an additional momentum factor UMD_t, defined as the difference in the returns of stocks with high (positive) momentum and those with low (negative) momentum.

[Table 1 here]

Independent of the specification, Hypothesis 1 is strongly supported: the estimates of π_i and γ_i are reliably negative while the estimates of λ_i are reliably positive. In words, following periods of unexpectedly increased market volatility, stock prices drop on average, controlling for the market-risk, the Fama-French, and momentum risk-factors. And, the prices of younger firms — with higher estimation risk — fall more than seasoned firms. Thus, the cross-section of returns is altered by an increase in the aggregate estimation risk along the lines predicted by our model. Moreover, the magnitude of the effect of market volatility innovations on the average contemporaneous excess stock returns is noteworthy, as we highlighted in the Introduction. But the ameliorating influence of firm age on the effects of volatility innovation are also striking.

Table 1 indicates an "age premium" in contemporaneous returns that is consistent with Barry and Brown (1984). Similarly, the average estimated coefficient of γ_i is consistent with the literature on asymmetric volatility, especially recent work that examines the effect of time-varying aggregate volatility on the cross-section of returns [e.g., Ang et al. (2006)]. However, the main contribution of our model is the prediction — based on the link between estimation risk of the market portfolio and market volatility — that the effect of volatility innovations in the cross-section will be itself influenced by the systematic estimation risk of individual assets (i.e., β_i^{ER}). The sign and significance of the average estimate of λ_i, when we use age of the firm as a proxy for β_i^{ER}, supports this prediction.

But, as we noted above, we can also test the annunciated prediction using the characteristics $\xi_{i1,t} = \text{B/M}_{it}$, $\xi_{i2,t} = \text{E/P}_{it}$, and $\xi_{i3,t} = \text{D/P}_{it}$. To do so, we obtain the data on the book-to-market, earnings-to-price, and dividend-to-price ratios from the merged CRSP-COMPUSTAT database during the period 1964-2004. Due to the more limited coverage of COMPUSTAT, the number of firms with data available on dividends, book value of equity, and earnings is 18,973, 16,771, and 8,187, respectively. We then estimate equation (16) after grouping the data into quintiles based on the values of these three ratios. The results are shown in Table 2.

[Table 2 here]

In the terminology of Hypothesis 2, Table 2 reports $\hat{\pi}_y$, $y = 1, 2, ...5$, when the loading on market volatility innovations is sorted according to the book-to-market, earnings-to-price, and dividend-to-price ratios. Hypothesis 2 is strongly supported by the data. For every characteristics, for each group, the average estimate $\hat{\pi}_y$ (the loading on market volatility innovation) is reliably negative. Moreover, $\hat{\pi}_y$ increases for higher book-to-market and earnings-to-price quintiles, i.e., the influence of market volatility innovations *falls* as the book-to-market and the earnings-to-price ratios increase, consistent with the view that firms with the major portion of equity value in uncertain growth options would be more susceptible to increases in aggregate estimation risk. We get essentially similar results for the dividend-to-price ratio (except for the first two quintiles); and, even here, the difference $(\hat{\pi}_1 - \hat{\pi}_5)$ is significant at 1% levels.

Overall, the evidence supports the theoretically-based hypothesis that market-volatility innovations are positively correlated with the estimation risk component of the market risk-premium; the evidence supports, as well, the hypothesis that the effect of these innovations on the cross-section of returns is driven by the systematic estimation risk of individual assets.

4.2 Oil Price Innovations and Cross-Section of Stock Returns

Economic intuition suggests that the variation in the aggregate estimation risk will also be driven by innovations in macroeconomic variables that affect the probability distribution of cash flows of a cross-section of firms. For example, changes in prices of factor inputs, such as oil, that are significant earnings drivers for firms in a variety of industries, and hence oil price innovations increase *uncertainty* about the expected performance of the aggregate economy.[14] However, our framework implies that the pricing effects of such oil price innovations on individual stocks will be *heterogeneous,* and will depend on their systematic estimation risk.

Thus, if we compare the cross-section of returns contemporaneous to oil price increases, then *ex post* we expect to find that firms whose returns are most negatively correlated with oil price increases will have lower contemporaneous excess returns, other things held fixed. Our model further predicts that the decline in returns will be increasing in the firms' systematic estimation risk (i.e., β_i^{ER}). We note that in addition to their impact on discount rates, oil price innovations also affect the expected value of future firm cash flows. Fortunately, the effect on cash flows can be disentangled from the effect on discount rates, through a judiciously chosen empirical test design

[14] We thank the referee for suggesting this example to us.

that we now describe.

We adopt a two-step testing procedure. For each, i, we first measure its exposure to crude oil price changes using 36-month rolling regressions of firm specific returns on innovations in oil prices:

$$r_{it} - r_{ft} = \alpha_i + \pi_i \delta(\text{Oil}_t) + \beta_i (r_{Mt} - r_{ft}), \tag{18}$$

where, $\delta(\text{Oil}_t)$ is the innovation in the oil price at the beginning of time-period t.

Now, it is important to distinguish between firms whose returns are positively versus negatively correlated with oil price innovations — the former are presumably firms that are net oil producers, while the latter are presumably firms that are net consumers of oil as a factor of production. Clearly, the consequences (for expected cash flows) of an unexpected oil price increase will be substantially different for oil producers versus net oil consuming firms. Therefore, at the beginning of each calendar year, we sort firms into deciles according to the value of the π_i coefficient estimated over the past three years, using equation (18). Note that decile-1 includes firms with the most negative estimates of π_i, i.e., firms whose returns are most *negatively* correlated with oil price increases (oil consumers), while decile 10 includes firms whose returns are most *positively* related to oil-price increases (oil producers).

Next, for each firm, we estimate in the current calendar year two models of contemporaneous stock price response to innovations in oil prices, after segregating such innovations according to their sign:

$$\begin{aligned} r_{it} - r_{ft} &= \alpha_i + \eta_i^- \delta(\text{Oil}_t^-) + \eta_i^+ \delta(\text{Oil}_t^+) + \beta_i (r_{Mt} - r_{ft}) && (19) \\ r_{it} - r_{ft} &= \alpha_i + \eta_i^- \delta(\text{Oil}_t^-) + \eta_i^+ \delta(\text{Oil}_t^+) + \gamma_i \text{ age}_{it} \\ &\quad + \lambda_i^- [\delta(\text{Oil}_t^-) * \text{age}_{it}] + \lambda_i^+ [\delta(\text{Oil}_t^+) * \text{age}_{it}] + \beta_i (r_{Mt} - r_{ft}), && (20) \end{aligned}$$

where, $\delta(\text{Oil}_t^-) = |\delta(Oil_t)|$ if $\delta(\text{Oil}_t) < 0$ and 0 else; and, $\delta(\text{Oil}_t^+) = \delta(Oil_t)$ if $\delta(\text{Oil}_t) > 0$, 0 otherwise. We then compute the average of the coefficients in (19)-(20) for each of the π_i-based deciles from equation (18).

Our model's empirical content resides in refutable predictions on the oil price innovations and the effect of firm age on these loadings, i.e., on the cross-sectional average of coefficients, $\hat{\eta}_y^-, \hat{\eta}_y^+, \hat{\lambda}_y^-, \hat{\lambda}_y^+$, $y = 1, ..., 10$.

For oil consumers (decile-1), an unexpected *increase* in oil prices causes a contemporaneous reduction in the expected value of future cash flows, and also a contemporaneous increase in the firm's cost of equity. The combined effect implies a reduction in the firm's market value and negative contemporaneous abnormal returns. By contrast, an unexpected *decrease* in oil prices has an asymmetrical impact. On the one hand, expected cash flows increase. On the other, the impact on the firm's cost of equity is ambiguous.[15] Thus, for oil consumers, a positive oil price innovation is associated with a contemporaneous decline in firm value, i.e., $\hat{\eta}_y^+ < 0$. But the change in firm value associated with a negative oil price innovation may be positive, zero, or less negative. Either way, it must always be the case that the coefficient $\hat{\eta}_y^+$ is lower that the coefficient $\hat{\eta}_y^-$, and this asymmetry forms the basis for our first empirical prediction.

An analogous analysis applies to oil producers (decile-10). There, the unambiguous effect occurs in the case of an unexpected *decrease* in oil prices, i..e, $\hat{\eta}_{10}^- < 0$. In this case, firm value drops due to a reduction in expected future cash flows and an increase in the firm's cost of equity. By contrast, an unexpected *increase* in oil prices has an ambiguous effect on firm value. The effect of the increase in expected cash flows is balanced by the ambiguous effect on discount rate, which leads to our second empirical prediction. For oil producers, it must be the case that the coefficient $\hat{\eta}_y^-$ is lower that the coefficient $\hat{\eta}_y^+$.[16]

Hypothesis 3 $\hat{\eta}_1^+ < 0$ *and* $(\hat{\eta}_1^+ - \hat{\eta}_1^-) < 0$. *Moreover,* $\hat{\eta}_{10}^- < 0$ *and* $(\hat{\eta}_{10}^+ - \hat{\eta}_{10}^-) > 0$.

Next, estimation risk perspective also predicts that, within the class of firms that are most sensitive to oil price innovations (i.e., decile-1 and decile-10), the effect of the oil price innovations will be less significant for *older* firms. That is,

Hypothesis 4 $\hat{\lambda}_1^+ > 0$ *and* $\hat{\lambda}_{10}^- > 0$.

4.2.1 Data and Returns

To test Hypotheses 3 and 4, we use data on monthly oil price innovations from 1981-2004, using West Texas Intermediate prices obtained from Dow Jones and Company. The stock data consist

[15] Since the cost of equity is an an affine function of $\left(\beta_{it}^{IR} + \beta_{it}^{ER}\right) R_{Mt}$ (cf. equation (10)), the effect of an oil price increase on the cost of equity depends on its influence on the market risk-premium (which is positive) and the intrinsic and estimation risk betas. But for an oil producer, the intrinsic or estimation risk betas may well be negatively related to oil prices, leaving the net effect of an increase in oil price on the the cost of equity as ambiguous.

[16] In general, for firms in decile-y, y = 2,...10, the restriction on the sign of $(\hat{\eta}_y^+ - \hat{\eta}_y^-)$ will depend on whether the returns of the average firm in that decile are negatively or positively correlated with oil price innovations. In particular, the sign will depend on the distribution of the firms with negative and positive return correlation (to oil price innovations). Since we are only confident that firms in the extreme deciles are all negatively and positively correlated with oil price innovations, these restrictions are annunciated for the extreme deciles only.

of the universe of firms available on CRSP during the sample period, and we require a minimum of 12 months of valid return observations per firm during each rolling 36-month window. This leaves a total of 18,993 firms available for this analysis.

The results are displayed in Table 3. Panel A displays the estimated coefficients for $\hat{\eta}_y^-$ and $\hat{\eta}_y^+$, $y = 1, ..., 10$, from equation (19). The associated *t-statistics* are also displayed. We also compute $(\hat{\eta}_y^+ - \hat{\eta}_y^-)$ for each decile, and provide the corresponding *t-statistics.* Panel B displays the estimates (and corresponding *t-statistics*) for $\hat{\eta}_y^-, \hat{\eta}_y^+, \hat{\lambda}_y^-, \hat{\lambda}_y^+$, for the lowest and the highest deciles, i.e., $y = 1$ and 10, from equation (20).

[Table 3 here]

In panel A, we find $\hat{\eta}_1^+ < 0$ at a high level of significance, which is consistent with Hypothesis 3. And because the higher deciles progressively include firms whose returns are less negatively or more positively correlated with oil price innovations, both the absolute magnitude of $\hat{\eta}_y^+$ and its statistical significance fall almost monotonically as we move upwards from deciles 2 through 10. For deciles 2-6, we find that the estimate of $\hat{\eta}_y^+$ is reliably negative, and in this range it is indeed the case that $\hat{\eta}_y^+ < \hat{\eta}_{y+1}^+$ (except for deciles 3 and 4). For the firms in the top deciles, we find that the estimates of $\hat{\eta}_y^-$ for deciles 8-10 are negative at high levels of significance, and the estimates for the top two deciles are significantly lower (i.e., more negative) than the estimates for the lower deciles. Finally, $(\hat{\eta}_1^+ - \hat{\eta}_1^-)$ is reliably negative and $(\hat{\eta}_{10}^+ - \hat{\eta}_{10}^-)$ is reliably positive; indeed, $(\hat{\eta}_y^+ - \hat{\eta}_y^-)$ is reliably negative for the lower deciles (deciles 1-5) and it is reliably positive for the higher deciles (i.e., deciles 8-10). Thus, the data substantially support Hypothesis 3.

In panel B, consistent with Hypothesis 4, we find that $\hat{\lambda}_1^+ > 0$ and $\hat{\lambda}_{10}^- > 0$ at high levels of significance. That is, within the class of firms that are most return-sensitive to oil price innovations, the adverse estimation risk effects of these innovations are exacerbated (ameliorated) for younger (older) firms.

4.3 Exchange Rate Innovations and Cross-Section of Stock Returns

The intuition underlying the "transmission-mechanism" from oil price innovations to effects on the cross-section of stock returns, analyzed in the previous section, should apply more generally for any macroeconomic shocks with significant cash flow consequences at the firm-level. Exchange rate innovations satisfy these requirements: they are clearly macroeconomic and will influence the cash flows of all firms with any exposure to foreign trade — either in their output or in their inputs [see, e.g., Solnik (1974), Grauer et al. (1976) and Adler and Dumas (1983)]. In principle, then, one can simply replicate the methodology that used in the previous section, by substituting oil price innovations with an appropriately defined empirical measure of exchange rate innovations.

Specifically, we use innovations in the foreign exchange rate — defined as the number of dollars per unit of foreign currency, measured against the trade-weighted exchange index (see below). As in the case of oil price innovations, one has to be careful in distinguishing the effects of an unexpected increase in the exchange rate (i.e., a devaluation of the dollar against the foreign currency) on firms that use foreign goods intensively (the 'importers') and firms who are more dependent on foreign sales than imports (the 'exporters'). Exchange rate increases will hurt the importers and improve the cash flow prospects of the exporters, and conversely for exchange rate decreases. Thus, the methodology we develop above in (18)-(20) is applicable in the case at hand, when we replace positive and negative oil price innovations, i.e., $\delta(\mathrm{Oil}_t^+)$ and $\delta(\mathrm{Oil}_t^-)$, with positive and negative foreign exchange rate innovations, denoted by $\delta(\mathrm{FX}_t^+)$ and $\delta(\mathrm{FX}_t^-)$. With this substitution, Hypotheses 3 and 4 also extend straightforwardly.

4.3.1 Data and Results

We use the Trade Weighted Exchange Index of Major Currencies published by the Board of Governors of the Federal Reserve System to obtain monthly exchange rates from 1973 through 2004. The stock data consist of the universe of firms available on CRSP during the sample period and we again require a minimum of 12 months of valid return observations per firm during each rolling 36-month window. This leaves a total of 20,992 firms available for the analysis.

The results are displayed in Table 4. Panel A displays the estimated loadings on the negative and positive exchange rate innovations, for each of the deciles that are sorted on the basis of sensitivity of firms' returns to exchange rate innovations. Panel B displays the estimates (and the corresponding *t-statistics*) for $\hat{\eta}_y^-, \hat{\eta}_y^+, \hat{\lambda}_y^-, \hat{\lambda}_y^+$, for the lowest and the highest deciles, i.e., $y = 1$ and 10, from the estimation of the regression equation that includes the effects of the firms' age (cf. equation (20)).

[Table 4 here]

In panel A, consistent with the theoretical predictions, we find that positive exchange rate innovations reliably reduce the contemporaneous excess stock returns of lower decile firms, i.e., the importers whose returns are most highly negatively correlated with dollar devaluations. On the other end of the spectrum, negative exchange rate innovations reliably reduce the contemporaneous excess stock returns for firms in the highest deciles, i.e., exporters whose returns are most negatively correlated with dollar revaluations. However, we do not find the size of these coefficients (i.e., $\hat{\eta}_y^+$ and $\hat{\eta}_y^-$) to behave as monotonically with respect to the deciles as in the case of the oil price innovations. Nonetheless, we still see a strong tendency for $(\hat{\eta}_y^+ - \hat{\eta}_y^-)$ to be negative for the lower deciles and be positive for higher deciles, which again supports the theoretical model.

In Panel B, we continue to find support for the theoretical prediction that within the class of firms that are most sensitive (in terms of returns) to foreign exchange rate innovations, the adverse estimation risk effects of such innovations are exacerbated (ameliorated) for younger (older) firms, other things held fixed. Note that both $\hat{\lambda}_1^+$ and $\hat{\lambda}_{10}^-$ are positive at high levels of significance.

Taken together, the observed effects of market-volatility, oil price, and foreign exchange rate innovations on the cross-section of equity returns provide substantial support for the hypothesis that the conditional covariance of mean returns is time-varying and is influenced by macroeconomic and market-wide factors in a manner consistent with an equilibrium model of estimation risk driven learning — through information of uncertain quality — by investors.

4.4 Innovations in the Dispersion of Analyst Opinions and Stock Returns

Turning, next, to the relationship between signal volatility or information spreads and the cross-section of returns derived in (13), we interpret the signals, s_{it}, as analysts' forecasts of expected earnings per share for firm i at the beginning of time-period t. Hence, signal volatility, ω_{it} (cf. (13)), is measured through the analysts' *dispersion of opinion,* using the coefficient of variation for analysts' annual forecasts estimated from I/B/E/S data, now part of Thompson Financial. The coefficient of variation is estimated by dividing the I/B/E/S reported standard deviation of analyst earnings/share forecasts for the current fiscal year end (I/B/E/S Fiscal Year period "1") by the absolute value of the mean earnings/share forecast, as listed in the I/B/E/S Summary History file. This proxy is typically used in the literature [e.g., Diether et al. (2002)].

The empirical prediction from our model is that the current returns will be negatively related to innovations in the coefficient of variation for analysts' annual forecasts. Calendar time portfolios are formed each month (t) of the calendar according to contemporaneous changes in the dispersion of analyst forecast occurring between month $t-1$ and month t. Portfolios are both equally weighted and value weighted according to the firm's market capitalization in the previous month. Changes in dispersion are divided into five equal quintiles. Each month of the calendar, a firm is placed into one of five different calendar time portfolios according to the value of its contemporaneous change in dispersion quintile. Firms that experienced the most positive innovation in dispersion of analyst forecast are placed in the portfolio corresponding to quintile 5. Firms with the most negative innovation are placed in quintile 1. The abnormal returns for each quintile portfolio are the intercept α from the following single factor regression:[17]

$$r_{qt} - r_{ft} = \alpha + \beta(r_{Mt} - r_{ft}) \tag{21}$$

where, r_{qt} is the rate of return of the portfolio corresponding to quintile q at time t. We will denote the average abnormal return in quintile, $q = 1, ...5$, by $\hat{\alpha}_q$.

To assess the statistical significance of the difference between $\hat{\alpha}_1$ and $\hat{\alpha}_5$, we form a hedge portfolio that takes long positions in quintile 1 stocks and short positions in quintile 5 stocks. Thus, the prediction here is that $\hat{\alpha}_1 > \hat{\alpha}_5$. The difference between $\hat{\alpha}_1$ and $\hat{\alpha}_5$ corresponds to the abnormal returns of the hedge portfolio, estimated as the intercept from the following regression:[18]

$$r_{1t} - r_{5t} = \alpha + \beta(r_{Mt} - r_{ft}), \tag{22}$$

where, r_{5t}, is the return of the portfolio corresponding to quintile 5 and r_{1t} similarly corresponds to quintile 1. Our model predicts that the abnormal returns in (22) will be *positive* because firms in quintile 5 (quintile 1) will have relatively low (high) contemporaneous returns, controlling for the specified priced risk-factors.

Hypothesis 5 *In the regression equation (21), $\hat{\alpha}_1 > \hat{\alpha}_5$, while in the regression equation (22), $\alpha > 0$.*

We also examine *firm-specific* stock price responses to contemporaneous innovations in dispersion of analyst forecast. For each firm, i, we estimate the following regression:

$$r_{it} - r_{ft} = \alpha_i + \pi_i \delta(\text{disp}_{it}) + \beta_i(r_{Mt} - r_{ft}) \tag{23}$$

[17] For robustness, we also estimate separate regressions for the three- and four-factor models previously employed.

[18] When $\hat{\alpha}_1$ and $\hat{\alpha}_5$ are obtained from the 3- or 4-factor models, the same models are used to estimate the intercept of the hedge portfolio.

where, r_{it}, is the rate of return for firm i at time t,and $\delta(\text{disp}_{it})$ is the change in dispersion of analyst forecast for firm i, between time $t-1$ and time t. Thus, our model predicts that,

Hypothesis 6 *In the regression equations (23), the cross-sectional average of π_i is negative.*

4.4.1 Data and Results

We collect data on all firms available on the I/B/E/S database from 1988-2002. In order to compute the dispersion in analyst forecasts, we restrict attention to firms covered by at least two analysts. This results in 8,462 firms with valid dispersion data. In Table 5, we report $\hat{\alpha}_q$ for both the equally- and value-weighted portfolio weights (cf. (21)), and also the abnormal returns, α, on the hedge portfolio (cf. (22)). (These results are presented at the bottom of the Table.) For robustness, we also provide estimates using the three-factor model of Fama and French (1992) as well as a four-factor model that includes UMD.

[Table 5 here]

Consistent with Hypothesis 5, the average abnormal returns $\hat{\alpha}_q$ fall significantly when we go from the quintiles with negative or low increases in analyst forecast dispersion to quintiles with the greatest increase in analyst dispersion. Also, the difference between $\hat{\alpha}_1$ and $\hat{\alpha}_5$ clearly is positive and statistically significant. This result is robust to controlling with either the three- or the four-factor asset pricing model.

In Table 6, we report the results of the firm-specific responses to innovations in analyst forecast dispersion (cf. (23)). Consistent with Hypothesis (6), the cross-sectional average of the estimates of π_i in (23) is negative and highly significant. Again, this result is robust to controlling for either the three- or four-factor asset pricing model.

[Table 6 here]

The results of Tables 5 and 6 indicate that *innovations* in the dispersion of analyst opinions help explain the cross-section of average stock returns, even after controlling for the risk factors currently employed in the literature. That is, innovations in the dispersion or volatility of *firm-specific* information appears to be a priced risk-factor. As we noted above, the role of innovations in signal volatility as priced risk-factors in the cross-section of returns is difficult to motivate in a world where the conditional variance of expected returns is known.[19]

4.5 Announcement Effects on Estimated Betas

Finally, to test the predictions on the announcement effects on firms' cost of capital, we focus market behavior around payout initiation by firms, which occurs through both dividends and share repurchases. Initiation of cash disbursements to shareholders is a watershed event in the life-cycle of the firm, and is duly noted as such by investors. While much of the literature has interpreted the dividend initiation announcement as affecting investors' expectations of future cash flows [e.g., Asquith and Mullins (1983) and Healy and Palepu (1988)],[20] a plausible case can be made that dividend and share repurchase initiations also signal a decline in the systematic (cash flow) risk of the firm [see, e.g., Grullon et al. (2001)]; i.e., these are corporate events that reduce the estimation risk of the stock, in the sense of Section 3.3.[21]

4.5.1 Data and Results

Dividend Initiations Dividend announcement dates and stock returns are obtained from the CRSP database. We select only the firm's first declared cash dividend classified by CRSP as having either monthly, quarterly, semiannual, annual, or unspecified payment frequency. We also require that at least 26-weeks of returns be available on CRSP prior to and following the week containing the dividend declaration date. Our sample covers the period from August 1963 through 2004 and includes 2017 firms.

For each sample firm i, we estimate the market model (14) independently for the 52-week period prior to, and the 52-week after, the week of the dividend repurchase initiation. The weekly firm and market returns are estimated by calculating the holding period returns for Thursday

[19] Miller (1977) argues that with heterogeneous beliefs and binding short-sale constraints, stocks will be overvalued, relative to the friction-free equilibrium, because asset prices will reflect only the beliefs of the optimistic investors. Hence, *if* the short-sale constraints are binding, then stocks with more heterogenous beliefs should have low expected returns. However, our empirical tests differ from Miller's world in several ways: we examine all stocks (and not necessarily short-sale constrained stocks) and focus on innovations in the dispersion of opinions when there is estimation risk. Interestingly, from a theoretical perspective, the presence of estimation risk reduces the so-called Miller-effect, because the optimistic or infra-marginal buyers are less aggressive in the presence of parameter uncertainty.

[20] See Boehme and Sorescu (2002) for a survey of the literature on the pricing effects of dividend initiations.

[21] Such an interpretation is consistent with the pecking-order theory of corporate finance [Myers (1984)]; it is also consistent with Lintner (1956), who emphasizes managerial risk-aversion in initiating payouts to shareholders that are unlikely to be maintained in the future.

through Wednesday, using CRSP daily returns. We denote the estimated beta from 52-week prior to (following) the event by $\hat{\beta}_i^-$ ($\hat{\beta}_i^+$). The corresponding standard errors are denoted by Std. Error($\hat{\beta}_i^-$) (Std. Error($\hat{\beta}_i^+$)). The hypothesis is then that:

Hypothesis 7 $\hat{\beta}_i^+ < \hat{\beta}_i^-$ *and Std. Error*($\hat{\beta}_i^+$) $<$ *Std. Error*($\hat{\beta}_i^-$).

The results of this empirical analysis are depicted in Table 7.

[Table 7 here]

In panel A, we begin by verifying the well known result that the Cumulative Abnormal Returns (CARs) are positive around dividend initiation dates, suggesting a substantial informational content associated with this type of an event. As is usual, the CARs are estimated by summing the relevant daily returns of the event firm during the announcement window and subtracting the corresponding return of the CRSP equally weighted market index, as explained in Brown and Warner (1985). The mean and median CARs for a three-day window centered on the initiation announcement day are both significantly positive.

Panel B reports the mean and median pre- and post-event beta estimates, along with their standard errors. Consistent with Hypothesis 7, we see that both the mean and median post-event betas and their standard errors are lower than their pre-event benchmarks, and the differences are highly significant. These results are of substantial interest to the dividend initiation literature, as we noted earlier in the paper.

Share Repurchase Initiations Share repurchase announcement dates are derived from the SDC Shares Repurchases database (from Thomson Financial) and, as before, we require that at least 26-weeks of returns be available on CRSP prior to and following the week containing the share repurchase declaration date. Our sample covers first-time share repurchases by firms during the period 1988-2004. It includes 3254 firms (or events). The testing procedure is analogous to that used for the dividend initiations, and the results are displayed in Table 8.

[Table 8 here]

The results in panel A indicate that payout initiations through repurchases have significant price effects and hence appear to have substantial information content. In panel B, we see that both the mean and median post-event betas are substantially lower than their pre-event benchmarks, and the differences are highly significant. Indeed, the median post-event beta is about 15 percent lower than the median pre-event beta. This panel also shows that the median standard errors of the beta estimates have fallen in a statistically significant fashion after the event.

Overall, our analysis indicates that in a world with uncertainty on the higher moments of returns and signals, major corporate events can have announcement effects by influencing the firm's systematic estimation risk, and thereby affecting the required rate of return.

5 Summary and Conclusions

It is a truism that investors are uncertain about the parameters of the return generating processes and use a variety of information sources to learn about these parameters. However, estimation risk typically goes hand-in-hand with uncertainty about information quality or precision. We have theoretically and empirically analyzed the effects of estimation risk on the cross-section of stock returns and firms' cost of capital when investors learn from information of uncertain quality, i.e., when investors are uncertain about the first and second moments of the joint distribution of returns and signals. With Normal-Wishart beliefs, the resultant equilibrium is a conditional CAPM in which assets are priced according to their systematic intrinsic and information-dependent — and hence *stochastic* — estimation risk. Moreover, the market risk-premium and volatility are also information-dependent, and hence stochastic.

We are able to derive and test empirical predictions from the model on the effects of both macroeconomic (or market-wide) and firm-specific information on the cross-section of returns. We also test the model's prediction that corporate events or disclosures that influence the stock's systematic estimation risk will have announcement effects by affecting the firm's cost of capital. The empirical results strongly support the predictions of the model. Our analysis not only yields new facts, but also sheds a different light on existing results. Market-wide and macroeconomic shocks that are correlated with shifts in market estimation risk — such as innovations in market volatility, oil prices, and the foreign exchange rate innovations — not only carry a statistically significant price of risk, but their influence on individual stock returns depends on the stock's systematic estimation risk — consistent with the basic predictions of the model. We also find that information-based and firm-specific risk factors such as dispersion in analysts' forecasts help explain the cross-section of returns. And, an event study on the announcement of dividend and share repurchase initiations finds statistically significant effects on the estimated betas and their standard errors, in the direction predicted by the model.

Our empirical analysis thus complements and adds to a growing literature that theoretically and empirically examines the role of information in asset pricing. While our starting point is estimation risk regarding expected returns, our contribution is to highlight the importance of information (on asset pricing) when investors are uncertain about the *higher* moments of the joint distribution of returns and signals. For example, while there are other possible interpretations of why market volatility innovations are priced in equilibrium [e.g., Ang et al. (2006)], to our knowledge there are few frameworks in the literature that would also be consistent with the interaction of volatility innovations with firm age and other proxies for firm-specific estimation risk that we find in our empirical analysis.

Our framework presents a rich agenda for future theoretical and empirical work. Clearly, we have considered only a subset of macroeconomic and firm-specific factors that are correlated with the market estimation risk-premium and the systematic estimation risk of individual stocks. But the information-dependent conditional covariance perspective employed here can be useful in developing other specifications of the conditional CAPM. Our event study related results can motivate development of a more systematic methodology to decompose announcements effects into changes in estimated cash flows versus estimation risk induced changes in the required rate of return. And, it will be interesting to examine if dynamic learning with a serially correlated information or signal process can provide an equilibrium explanation for the widely studied post-information-event equity price drifts [e.g., Ball and Brown (1968), Michaely et al. (1995) and Brav and Heaton (2002)].

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Table 1: Firm-specific stock price responses to contemporaneous innovations in market volatility as a function of firm age.

For each firm listed on CRSP, *i*, we estimate the following three regressions:

(a) CAPM $r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(\sigma^2_{Mt}) + \gamma_i\, age_{it} + \lambda_i\, [\delta(\sigma^2_{Mt})*age_{it}] + \beta_i\, (r_{mt} - r_{ft})$

(b) 3-Factor $r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(\sigma^2_{Mt}) + \gamma_i\, age_{it} + \lambda_i\, [\delta(\sigma^2_{Mt})*age_{it}] + \beta_i\, (r_{mt} - r_{ft}) + s_i\, SMB_t + h_i\, HML_t$

(c) 4-Factor $r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(\sigma^2_{Mt}) + \gamma_i\, age_{it} + \lambda_i\, [\delta(\sigma^2_{Mt})*age_{it}] + \beta_i\, (r_{mt} - r_{ft}) + s_i\, SMB_t + h_i\, HML_t + u_i\, UMD_t$

where $\delta(\sigma^2_{Mt})$ is the innovation in the volatility of the value-weighted market index at time *t*, age_{it} is the natural logarithm of firm's *i* age at time *t* (measured as the number of months the firm has been listed in CRSP), $\delta(\sigma^2_{Mt})*age_{it}$ is the interaction of the previous two terms, r_{it} is the rate of return for firm *i* at time *t*, r_{ft} is the rate of return on a one-month Treasury bill at time *t*, r_{Mt} is the value-weighted return of the stock market at time *t*, SMB_t is difference in returns between portfolios of large stocks and portfolios of small stocks, HML_t is the difference in returns between portfolios of stocks with high book-to-market ratios and those with low book-to-market, and UMD_t is the difference in the returns of stocks with high (positive) momentum and those with low (negative) momentum. Shown below are the cross-sectional averages of firm specific coefficients π_i, γ_i, and λ_i, for each of the three models, with t-statistics computed in the cross-section. The sample period is from 1964 to 2004.

Model estimated	Cross-sectional average of π_i, the coefficient of $\delta(\sigma^2_{Mt})$		Cross-sectional average of γ_i, the coefficient of age_{it}		Cross-sectional average of λ_i, the coefficient of $[\delta(\sigma^2_{Mt})*age_{it}]$	
	Point estimate	t-stat	Point estimate	t-stat	Point estimate	t-stat
(a) CAPM	-7.7146	-6.57***	-0.009509	-7.85***	1.6294	7.77***
(b) 3-Factor	-4.2981	-2.81***	-0.008296	-5.37***	1.0977	4.17***
(c) 4-Factor	-5.1023	-3.37***	-0.009085	-5.79***	1.1838	4.54***

***, Statistically different from zero at the one percent significance level.

Table 2: Firm-specific stock price responses to contemporaneous innovations in market volatility as a function of firm dividend-to-price ratio, earnings-to-price ratio and book-to-market ratio.

For each firm listed on CRSP, *i*, we group firms into quintiles alternatively using three different criteria:

(a) dividend-to-price ratio, (b) earnings-to-price ratio, and (c) book-to-market ratio for the duration of the firm's lifetime. Firm returns are classified into quintiles depending on the value of the signal noise proxy during the preceding month. Within each quintile we estimate the following regression:

$$r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(\sigma^2_{Mt}) + \beta_i\, (r_{Mt} - r_{ft})$$

where, $\delta(\sigma^2_{Mt})$ is the innovation in the volatility of the value-weighted market index at time *t*, r_{it} is the rate of return for firm *i* at time *t*, r_{ft} is the rate of return on a one-month Treasury bill at time *t*, and r_{Mt} is the value-weighted return of the stock market at time *t*. Panel A presents the results for quintile sorts based on dividend-to-price ratios. Panel B presents results for quintile sorts based on earnings-to-price ratios. Panel C presents results for quintile sorts based on book-to-market ratios. T-statistics are shown in brackets under each parameter. The sample period is from 1964 to 2004.

Quintile 1 (Lowest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Highest)	**Difference: Quintile 1 minus Quintile 5**
Panel A: Value of π_i as a function of the book-to-market quintile					
-0.9106	-0.7377	-0.5792	-0.4619	-0.1092	**-0.8013**
*[-7.69]****	*[-6.99]****	*[-6.37]****	*[-4.78]****	*[-0.77]*	***[-4.34]******
Panel B: Value of π_i as a function of the earnings-to-price quintile					
-0.5204	-0.3415	-0.3154	-0.1451	-0.1695	**-0.3510**
*[-3.45]****	*[-2.70]****	*[-3.05]****	*[-1.35]*	*[-1.13]*	***[-1.65]****
Panel C: Value of π_i as a function of the dividend-to-price quintile					
-0.9043	-0.9865	-0.8205	-0.6080	-0.2220	**-0.6823**
*[-7.80]****	*[-9.80]****	*[-8.66]****	*[-6.21]****	*[-1.84]**	***[-4.08]******

***, **, * Statistically different from zero at the one, five and ten percent significance level respectively.

Table 3: Firm-specific stock price responses to contemporaneous innovations in crude oil prices as a function of firm past sensitivity to innovations in crude oil prices.

For each firm listed on CRSP, *i*, we first measure its exposure to crude oil price changes using 36-month rolling regressions of firm specific returns on innovations in oil prices:

$$r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(OIL_t) + \beta_i\, (r_{Mt}-r_{ft}) \qquad (1)$$

where $\delta(OIL_t)$ is the innovation in the oil price at *t*, r_{it} is the rate of return for firm *i* at time *t*, r_{ft} is the rate of return on a one-month Treasury bill at time *t*, r_{Mt} is the value-weighted return of the stock market at time *t*. At the beginning of each calendar year, we sort firms into deciles according to the value of the π_i coefficient measured over the past three years using equation (1). (*Note that decile-1 includes firms with the most negative estimates of* π_i, *while decile-10 includes firms with the most positive estimates of* π_i). Then, for each firm in the current calendar year we estimate two models of contemporaneous stock price response to innovations in oil prices, after segregating such innovations according to their sign:

$$r_{it} - r_{ft} = \alpha_i + \eta_i^-\, \delta(OIL^-_t) + \eta_i^+\, \delta(OIL^+_t) + \beta_i\, (r_{Mt}-r_{ft})\ ;\ \text{and} \qquad (2)$$

$$r_{it} - r_{ft} = \alpha_i + \eta_i^-\, \delta(OIL^-_t) + \eta_i^+\, \delta(OIL^+_t) + \gamma_i\, age_{it} + \lambda_i^-\, [\delta(OIL^-_t)*age_{it}] + \lambda_i^+\, [\delta(OIL^+_t)*age_{it}] + \beta_i\, (r_{Mt}-r_{ft}) \qquad (3)$$

where $\delta(OIL^+_t)$ equals $\delta(OIL_t)$ if $\delta(OIL_t) > 0$, and zero otherwise; $\delta(OIL^-_t)$ equals ABS[$\delta(OIL_t)$] if $\delta(OIL_t) < 0$, and zero otherwise; and, age_{it} is the natural logarithm of firm's *i* age at time *t*, measured as the number of months the firm has been listed in CRSP. Panel A shows the average value of coefficients η_i^+ and η_i^- from equation (2), for each π_i-decile, along with corresponding t-statistics. Also shown is a test of statistical significance of the difference between the two. Panel B shows the average value of η_i^+ and λ_i^+ from equation (3), for firms in the lowest π_i-decile, and the average value of η_i^- and λ_i^- for firms in the highest π_i-decile, together with the value of the age coefficient (γ_i). The sample period is from 1981 to 2004.

Panel A: Cross-sectional average of coefficients η_i^+ and η_i^- from equation (2)

π-sorted deciles from equation (1)	Cross-sectional average of η_i^+, the coefficient of $\delta(OIL^+)$		Cross-sectional average of η_i^-, the coefficient of $\delta(OIL^-)$		Difference in cross-sectional averages of η_i^+ and η_i^-	
	Point estimate	t-stat	Point estimate	t-stat	Point estimate	t-stat
1 (consumers)	-0.1763	-7.10***	-0.1125	-4.37***	-0.0638	-2.49**
2	-0.1281	-5.62***	-0.0221	-1.03	-0.1060	-5.39***
3	-0.0752	-4.48***	0.0120	0.71	-0.0873	-5.13***
4	-0.0819	-5.75***	0.0164	1.00	-0.0982	-6.32***
5	-0.0406	-3.20***	0.0131	0.90	-0.0538	-3.90***
6	-0.0345	-2.53**	-0.0074	-0.51	-0.0272	-1.84*
7	0.0024	0.17	-0.0190	-1.23	0.0214	1.35
8	0.0067	0.43	-0.1063	-5.67***	0.1130	6.36***
9	-0.0068	-0.33	-0.2308	-11.26***	0.2240	10.53***
10 (producers)	0.0080	0.31	-0.2889	-10.70***	0.2969	11.49***

***, **, * Statistically different from zero at the one, five and ten percent significance level respectively.

Table 3 (continued)

Panel B: Cross-sectional average of coefficients η_i^+, λ_i^+, η_i^- and λ_i^- from equation (3)

	Sub-sample			
	Lowest π_i-decile from equation (1)		Highest π_i-decile from equation (1)	
	Coefficient Value	t-statistic	Coefficient Value	t-statistic
Cross-sectional average of η_i^+, the coefficient of $\delta(OIL^+)$	-14.18	-3.89***		
Cross-sectional average of λ_i^+, the coefficient of $[\delta(OIL^+)*age]$	2.79	4.50***		
Cross-sectional average of η_i^-, the coefficient of $\delta(OIL^-)$			-13.69	-6.81***
Cross-sectional average of λ_i^-, the coefficient of $[\delta(OIL^-)*age]$			2.80	7.39***
Cross-sectional average of γ_i, the coefficient of age	-0.1045	-4.21***	-0.0720	-3.55***

***, **, * Statistically different from zero at the one, five and ten percent significance level respectively.

Table 4: Firm-specific stock price responses to contemporaneous innovations in foreign exchange rates as a function of firm past sensitivity to innovations in foreign exchange.

For each firm listed on CRSP, *i*, we first measure its exposure to foreign exchange risk through 36-month rolling regressions of firm specific returns on foreign exchange innovations:

$$r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(FX_t) + \beta_i\, (r_{Mt}-r_{ft}) \quad (1)$$

where $\delta(FX_t)$ is the innovation in the foreign exchange rate at *t*, r_{it} is the rate of return for firm *i* at time *t*, r_{ft} is the rate of return on a one-month Treasury bill at time *t*, r_{Mt} is the value-weighted return of the stock market at time *t*. Foreign exchange rate is defined as the number of dollars per unit of foreign currency, measured against the trade weighted exchange index. At the beginning of each calendar year, we sort firms into deciles according to the value of the π_i coefficient measured over the past three years using equation (1). (*Note that decile-1 includes firms with the most negative estimates of π_i, while decile-10 includes firms with the most positive estimates of π_i*). Then, for each firm in the current calendar year we estimate two models of contemporaneous stock price response to innovations in foreign exchange risk, after segregating such innovations according to their sign:

$$r_{it} - r_{ft} = \alpha_i + \eta_i^-\, \delta(FX^-_t) + \eta_i^+\, \delta(FX^+_t) + \beta_i\, (r_{Mt}-r_{ft}) \text{ ; and} \quad (2)$$

$$r_{it} - r_{ft} = \alpha_i + \eta_i^-\, \delta(FX^-_t) + \eta_i^+\, \delta(FX^+_t) + \gamma_i\, age_{it} + \lambda_i^-\, [\delta(FX^-_t)*age_{it}] + \lambda_i^+\, [\delta(FX^+_t)*age_{it}] + \beta_i\, (r_{Mt}-r_{ft}) \quad (3)$$

where $\delta(FX^+_t)$ equals $\delta(FX_t)$ if $\delta(FX_t) > 0$, and zero otherwise; $\delta(FX^-_t)$ equals $ABS[\delta(FX_t)]$ if $\delta(FX_t) < 0$, and zero otherwise; and, age_{it} is the natural logarithm of firm's *i* age at time *t*, measured as the number of months the firm has been listed in CRSP. Panel A shows the average value of coefficients η_i^+ and η_i^- from equation (2), for each π_i-decile, along with corresponding t-statistics. Also shown is a test of statistical significance of the difference between the two. Panel B shows the average value of η_i^+ and λ_i^+ from equation (3), for firms in the lowest π_i-decile, and the average value of η_i^- and λ_i^- for firms in the highest π_i-decile, together with the value of the age coefficient (γ_i). The sample period is from 1973 to 2004.

Panel A: Cross-sectional average of coefficients η_i^+ and η_i^- from equation (2)

π-sorted deciles from equation (1)	Cross-sectional average of η_i^+, the coefficient of $\delta(FX^+)$		Cross-sectional average of η_i^-, the coefficient of $\delta(FX^-)$		Difference in cross-sectional averages of η_i^+ and η_i^-	
	Point estimate	t-stat	Point estimate	t-stat	Point estimate	t-stat
1 (importers)	-0.1913	-1.99**	-0.0301	-0.35	-0.1612	-1.68*
2	-0.4557	-6.51***	-0.0397	-0.61	-0.4159	-5.94***
3	-0.3640	-5.88***	-0.1844	-3.17***	-0.1796	-2.88***
4	-0.3262	-5.69***	-0.2149	-4.21***	-0.1113	-1.99**
5	-0.1660	-3.23***	-0.1368	-2.81***	-0.0293	-0.55
6	-0.2528	-5.20***	-0.2355	-5.10***	-0.0173	-0.36
7	-0.1469	-2.55***	-0.3036	-5.44***	0.1567	2.68***
8	-0.2611	-3.94***	-0.3211	-4.95***	0.0600	0.97
9	-0.0935	-1.20	-0.3050	-3.94***	0.2115	2.56***
10 (exporters)	-0.1331	-1.39	-0.3433	-3.74***	0.2102	2.17**

***, **, * Statistically different from zero at the one, five and ten percent significance level respectively.

Table 4 (continued)

Panel B: Cross-sectional average of coefficients η_i^+, λ_i^+, η_i^- and λ_i^- from equation (3)

	Sub-sample			
	Lowest π_i-decile from equation (1)		Highest π_i-decile from equation (1)	
	Coefficient Value	t-statistic	Coefficient Value	t-statistic
Cross-sectional average of η_i^+, the coefficient of $\delta(FX^+)$	-46.36	-6.73 ***		
Cross-sectional average of λ_i^+, the coefficient of $[\delta(FX^+)*age]$	9.75	7.49 ***		
Cross-sectional average of η_i^-, the coefficient of $\delta(FX^-)$			40.57	-6.39***
Cross-sectional average of λ_i^-, the coefficient of $[\delta(FX^-)*age]$			8.91	7.26***
Cross-sectional average of γ_i, the coefficient of age	-0.0796	-6.09***	-0.0766	-6.48***

***, **, * Statistically different from zero at the one, five and ten percent significance level respectively.

Table 5: Returns to portfolios formed on contemporaneous innovations in dispersion of analyst forecasts

Calendar time portfolios are formed each month (t) of the calendar according to contemporaneous changes in the dispersion of analyst forecast occurring between month *t-1* and month t. Portfolios are both equally weighted and value weighted according to the firm's market capitalization in the previous month. Changes in dispersion are divided into five equal quintiles. Each month of the calendar, a firm is placed into one of five different calendar time portfolios according to the value of its contemporaneous change in dispersion quintile. Firms that experienced the most positive innovation in dispersion of analyst forecasts are placed in quintile 5. Firms with the most negative innovation are placed in quintile 1. The hedge portfolio at the bottom of the table takes long positions in the quintile 1 portfolio and short positions in the quintile 5 portfolio. The abnormal returns for each quintile portfolio are the intercept (α) from either (a) the one-factor CAPM, (b) the Fama-French three-factor model, or (c) the four-factor model that includes the momentum term UMD. The latter is represented by the following regression; the other two models are just reduced forms of this equation:

$$r_{qt} - r_{ft} = \alpha + \beta\,(r_{mt} - r_{ft}) + s\,SMB_t + h\,HML_t + u\,UMD_t$$

where, r_{qt}, is the rate of return of the portfolio corresponding to quintile q at time t, r_{ft} is the rate of return on a one-month Treasury bill at time t, r_{Mt} is the value-weighted return of the stock market at time t, SMB_t is difference in returns between portfolios of large stocks and portfolios of small stocks, HML_t is the difference in returns between portfolios of stocks with high book-to-market ratios and those with low book-to-market, and UMD_t is the difference in the returns of stocks with high (positive) momentum and those with low (negative) momentum. Portfolios are rebalanced monthly.

The abnormal returns of the hedge portfolio are estimated with either the following regression, or the appropriate reduced form corresponding to the CAPM or three-factor model:

$$r_{1t} - r_{5t} = \alpha + \beta\,(r_{mt} - r_{ft}) + s\,SMB_t + h\,HML_t + u\,UMD_t$$

where r_{5t} is return of the portfolio corresponding to quintile 5 and r_{1t} corresponds to quintile 1. The sample period is from 1987 to 2002.

Model estimated	Dispersion change quintile	Portfolio weight			
		Equally-weighted		Value-weighted	
		Abnorm. Ret. (%)	t-stat	Abnorm. Ret. (%)	t-stat
(a) CAPM	1 (decreases)	0.12%	0.45	-0.14%	-0.98
	2	0.85%	5.39***	0.43%	3.91***
	3	0.19%	0.84	0.30%	3.16***
	4	-0.06%	-0.31	-0.16%	-1.15
	5 (increases)	-0.95%	-3.55***	-0.70%	-4.86***
(b) Three-factor model	1 (decreases)	0.05%	0.32	-0.11%	-0.79
	2	0.71%	5.91***	0.45%	4.25***
	3	0.13%	1.01	0.34%	3.73***
	4	-0.25%	-1.58	-0.22%	-1.59
	5 (increases)	-1.05%	-6.84***	-0.69%	-5.34***
(c) Four-factor model	1 (decrease)	0.43%	3.63***	0.02%	0.12
	2	0.92%	8.35***	0.31%	3.02***
	3	0.41%	3.74***	0.21%	2.41**
	4	0.09%	0.67	-0.23%	-1.56
	5 (increases)	-0.61%	-5.83***	-0.55%	-4.30***
Hedge portfolio					
(a) CAPM	1 minus 5	1.07%	11.73***	0.56%	3.27***
(b) Three-factor	1 minus 5	1.10%	11.86***	0.58%	3.16***
(c) Four-factor	1 minus 5	1.04%	10.92***	0.57%	3.16***

***, ** Statistically different from zero at the one and five percent significance level, respectively.

Table 6: Firm-specific stock price responses
to contemporaneous innovations in dispersion of analyst forecasts

For each firm, *i*, we estimate, alternatively, the following three regressions using monthly data:

$$r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(disp_{it}) + \beta_i\, (r_{mt} - r_{ft}) \qquad \text{(a)}$$

$$r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(disp_{it}) + \beta_i\, (r_{mt} - r_{ft}) + s_i\, SMB_t + h_i\, HML_t \qquad \text{(b)}$$

$$r_{it} - r_{ft} = \alpha_i + \pi_i\, \delta(disp_{it}) + \beta_i\, (r_{mt} - r_{ft}) + s_i\, SMB_t + h_i\, HML_t + u_i\, UMD_t \qquad \text{(c)}$$

where, r_{it} is the rate of return for firm *i* at time *t*, r_{ft} is the rate of return on a one-month Treasury bill at time *t*, r_{Mt} is the value-weighted return of the stock market at time *t*, SMB_t is difference in returns between portfolios of large stocks and portfolios of small stocks, HML_t is the difference in returns between portfolios of stocks with high book-to-market ratios and those with low book-to-market, and UMD_t is the difference in the returns of stocks with high (positive) momentum and those with low (negative) momentum. $\delta(disp_{it})$ is the change in dispersion of analyst forecast for firm *i*, between time *t-1* and time *t*. Shown below is the cross-sectional average of firm specific coefficients π_i, with t-statistics computed in the cross-section. The sample period is from 1987 to 2002.

Model estimated	Cross-sectional average of π_i, the coefficient of $\delta(disp_{it})$	
	Point estimate	t-stat
(a) CAPM	-0.04363	-5.29***
(b) Three-factor Model	-0.03958	-4.66***
(c) Four-factor Model	-0.03484	-4.16***

***, Statistically different from zero at the one percent significance level.

Table 7: Effects of dividend initiation announcements on cost of capital

Panel A: Cumulative Abnormal Returns around announcement dates

Mean and median Cumulative Abnormal Returns (CARs) are reported for firms announcing dividend initiations. CARs are measured for a three-day window centered on the initiation announcement day. Results are reported for the entire sample of 2017 firms. CARs are estimated by summing the relevant daily returns of the event firm during the announcement window and subtracting corresponding return of the CRSP equally weighted market index, as explained in Brown and Warner (1985); t-statistics and p-values are shown in brackets, for mean and median CARs, respectively.

Statistic	Cumulative Abnormal Returns
Mean	0.02929 *[t=16.87]******
Median	0.01639 *[p<0.0001]******

***, **, * Significantly different from zero at the 1%, 5%, and 10% level, respectively (two tail test).

Panel B: Changes in beta and its estimation error around announcement dates

Pre- and post- dividend initiation announcement betas and estimation errors are calculated using the following OLS market model:

$$r_{it} = \alpha_i + \beta_i r_{Mt} + e_{it}$$

Two independent OLS regressions are estimated for each of the 2017 sample firms: (1) the 52-week period before and (2) the 52-week period after the dividend initiation announcement window. The weekly firm and market returns are estimated by calculating the holding period returns for Thursday through Wednesday, using CRSP daily returns. At least 26 weeks of returns are required in both the pre- and post-announcement periods. The mean and median pre- and post-announcement betas (β) and estimation errors of beta (σ_β^2) are reported below. The estimation error (σ_β^2) is the standard error of β in the above regression. Also reported are the mean changes in beta and estimation errors across the pre- and post-announcement periods, along with t-statistics (calculated cross-sectionally), and the corresponding median changes along with and p-values.

Statistic	Beta (β)			Estimation error of beta (σ_β^2)		
	Before	After	Change (Δ)	Before	After	Change (Δ)
Mean	1.10242	1.05898	-0.04344 *[t=-2.07]****	0.54839	0.52946	-0.01893 *[t=-3.20]****
Median	1.06065	1.03092	-0.04552 *[p=0.0112]***	0.47946	0.47304	-0.00887 *[p=0.0024]****

***, **, * Significantly different from zero at the 1%, 5%, and 10% level, respectively (two tail test).

Table 8: Effects of stock repurchase initiation announcements on cost of capital

Panel A: Cumulative Abnormal Returns around announcement dates

Mean and median Cumulative Abnormal Returns (CARs) are reported for firms announcing stock repurchases for the first time. CARs are measured for a three-day window centered on the repurchase announcement day. Results are reported for the entire sample of 3254 firms. CARs are estimated by summing the relevant daily returns of the event firm during the announcement window and subtracting corresponding return of the CRSP equally weighted market index, as explained in Brown and Warner (1985); t-statistics and p-values are shown in brackets, for mean and median CARs, respectively.

Statistic	Cumulative Abnormal Returns
Mean	0.03018 *[t=15.87]******
Median	0.01849 *[p<0.0001]******

***, **, * Significantly different from zero at the 1%, 5%, and 10% level, respectively (two tail test).

Panel B: Changes in beta and its estimation error around announcement dates

Pre- and post repurchase-announcement betas and estimation errors are calculated using the following OLS market model:

$$r_{it} = \alpha_i + \beta_i r_{Mt} + e_{it}$$

Two independent OLS regressions are estimated for each of the 3254 sample firms: (1) the 52-week period before and (2) the 52-week period after the repurchase announcement window. The weekly firm and market returns are estimated by calculating the holding period returns for Thursday through Wednesday, using CRSP daily returns. At least 26 weeks of returns are required in both the pre- and post-announcement periods. The mean and median pre- and post-announcement betas (β) and estimation errors of beta (σ_β^2) are reported below. The estimation error (σ_β^2) is the standard error of β in the above regression. Also reported are the mean changes in beta and estimation errors across the pre- and post-announcement periods, along with t-statistics (calculated cross-sectionally), and the corresponding median changes along with and p-values.

Statistic	Beta (β)			Estimation error of beta (σ_β^2)		
	Before	After	Change (Δ)	Before	After	Change (Δ)
Mean	0.9479	0.81686	-0.13024 *[t=-7.89]******	0.50641	0.49543	-0.01098 *[t=-2.27]****
Median	0.84503	0.71833	-0.12313 *[p<0.0001]******	0.43329	0.41484	-0.02005 *[p<0.0001]******

***, **, * Significantly different from zero at the 1%, 5%, and 10% level, respectively (two tail test).