Asset Pricing Theory with an Imprecise Information Set[*]

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Abstract

This paper provides a novel theoretical platform for the pricing of imprecise accounting information as a systematic market risk. Our intertemporal asset pricing model shows that systematic information-quality risk is priced through a distinct market risk premium and three extra betas associated with an imprecise-information risk. Our first information-quality beta is related to the covariance between market-wide imprecise-information return error and security precise return. Together with the separate market information-quality risk premium, this beta provides the theoretical underpinning for a separate market information-quality factor in the spirit of empirical multiple-factor model prevalent in the literature. The second extra beta (linked to the covariance between firm and market-wide imprecise-information return errors), represents the commonality in information quality, which is priced by investors seeking to curtail adverse effects of imprecise accounting information on their portfolio value. Our third information-quality beta (related to the covariance between stock imprecise-information return error and overall market return), implies that – for hedging purposes – investors prefer to invest in stocks issued by firms that tend to, erroneously or deliberately, release false positive information about the firm when the market is bearish. Our model is strongly supported by empirical evidence.

1. Introduction

Traditional asset-pricing models are based on the assumption that the financial market is informationally efficient and that individuals are well informed (see for example, Sharpe, 1964; Lintner 1965; Mossin, 1966; and Merton, 1973). However, there is substantial evidence indicating that information releases are noisy (see for example, Faust, Rogers, and Wright, 2000; Shapiro and Wicox, 1999; and Wang 1993). With an imprecise information set, investors may face information-quality (information-imprecision) risk. Ignoring this risk may lead to asset mispricing in traditional asset-pricing models. This paper provides a theoretical platform for the pricing of imprecise accounting information as a systematic market risk factor.

There is a growing body of literature that examines the pricing of different manifestations of an imperfect information set, both theoretically and empirically. For example, Easley and O'Hara (2004) derive a rational-expectations model under which asset returns are affected by the information asymmetry between privately informed and publically informed (uninformed) investors. This model implies that, while privately informed investors adjust their portfolios based on the arrival of private information, uninformed investors hold *ex-ante* underperforming portfolios. Therefore, uninformed investors face systematic asymmetric information risk for which they demand a risk premium. In addition, this model also implies that investors demand higher asset returns for facing imprecise information. These theoretical predictions suggest that higher accounting-information precision reduces the asset risk for uninformed investors, and thus results in a lower cost of capital. Consequently, numerous studies empirically test the relation between accounting-information precision and the cost of equity capital and/or the cost of debt capital.[1]

Francis , LaFont, Olsson, and Schipper (2004) and Botosan , Plumlee, and Xie (2004) relate the cost of equity of a firm to the firm's information quality. Consistent with the prediction of Easley and O'Hara (2004) that information precision is non-diversifiable, Francis et al. (2005) show that poorer market-wide accrual-quality factor as

[1] See for example, Francis LaFont, Olsson, and Schipper (2004, 2005), Botosan, Plumlee, and Xie (2004), Aboody, Hughes.and Liu (2005), Liu and Wysocki (2006), Core et al. (2008), Ogneva (2008), and Kravet and Shevlin (2010) for studies focusing on the cost of equity capital. As for studies looking at the cost of debt capital, see Francis et al. (2005) Anderson et al. (2004), Graham et al. (2008), and Bhojraj and Swaminathan (2007). For a survey of this line of literature see Dechow, Ge, and Schrand (2010).

a measure of an information-quality factor is associated with a larger cost of equity capital. In other words, firms are exposed to information precision risk with a significantly positive factor loading with respect to their market-wide information-quality factor, after controlling for the Fama and French (1993) three factors.

A follow up study by Core, Guaya, and Verdi (2008) confirms that the time-series regressions of stock returns on cotemporaneous factor returns used by Francis et al. (2005) yield an average positive factor loading with respect to the market information-quality factor. However, after running a cross-sectional regression of stock returns on the estimated (time-series) information-quality factor loadings (while controlling for the Fama and French three factor loadings), they show that investors do not demand a return premium for this positive exposure to information imprecision. Stated differently, information quality is not a priced market factor as implied by Easley and O'Hara (2004) model.

More recent research challenges the conclusion of Core et al. (2008), and demonstrates that information precision is priced under certain market conditions. Kravet and Shevlin (2010) use the Fama and French (1993) three-factor model, augmented by two information precision factors: a market innate accrual quality factor and market discretionary component of accrual quality factor. Their findings indicate that during a short period following accounting restatement, higher discretionary precision factor loadings yield a higher cost of equity capital at the cross section of restatement firms. I.e., information precision risk is priced for restatement firms following the restatement announcement. Moreover, they show that the discretionary component of information risk is also priced at the cross section of firms in the same industries as the restatement firms.

Ogneva (2008) claims that Core et al.'s (2008) rejection of information precision as a priced market factor comes about because lower information-quality firms suffer from negative future cash flow shocks which depress future returns. Overall, this may offset the higher returns one would expect for low information-quality firms.[2] Her

[2] When controlling for cash flow shocks in the Core et al.'s (2008) regression model, Ogneva (2008) finds that stock returns become significantly and positively related to the information-quality factor loadings at the cross section. She introduces an additional test, which replaces the standard accrual-quality measure of Dechow and Dichev (2002) by a measure of accrual quality, scaled by the average of absolute accruals

findings indicate that, after properly controlling for the impact of accrual quality on future cash-flow shocks, investors demand a return premium for a positive exposure (factor loading) with respect to information imprecision. I.e., the information-quality risk factor is priced.

While there is some empirical evidence that an information-precision factor is systematic and priced, there is still lack of theoretical underpinning for its inclusion in an asset-pricing model as a separate market factor. To the best of our knowledge, the only two papers incorporating accounting-information precision in an asset-pricing model are those of Lambert, Leuz, and Verrecchia (2007) and Lambert, Leuz, and Verrecchia (2012).

The former paper is a pioneer theoretical study on the pricing of imprecise information, and the latter presents the first model to show that imprecise accounting information alters systematic risk and affects asset prices at the cross section. Note that, neither paper provides a theoretical justification for the pricing of an information-quality factor separate from the Capital Asset Pricing Model (CAPM) market factor. Our paper complements this literature by providing a theoretical foundation for the pricing of imprecise accounting information as a systematic market factor.

Of these two papers, our paper is most closely related to that of Lambert et al. (2007) who derive a one-period CAPM-based model to study the effects of imprecise accounting information on the cost of capital. In their model, lower precision of accounting information about the firm's future cash flow increases its conditional covariance with market cash flows (or the firm's conditional cash-flow beta) and consequently increases the cost of equity. Therefore, the cross-sectional pricing of information risk in the Lambert et al. (2007) model is manifested through the imprecise-information induced measurement error in the estimation of the firm's cash-flow beta.[3]

estimated over the previous five years. This new measure is less correlated with future cash flow shocks. When she replaces the standard accrual-quality measure with her scaled measure in the Fama and MacBeth (1973) procedure used by Core et al. (2008), she finds that the cost of equity capital is significantly and positively related to her modified accrual-quality factor.

[3] In somewhat related finance literature on estimation risk, the source of information about a firm comes from its historical time-series of returns (see for example, Barry and Brown, 1985; and Coles et al., 1995). Lambert et al. (2007) note that the reliance in this literature on the time-series of returns as the source of information affects a significant portion of the covariance structure. Different from their model, in this stream of research "new information is correlated conditionally with contemporaneous observations and

Lambert et al. note that this result has strong implications for empirical asset-pricing studies incorporating imprecise information. However, their model does not provide the theoretical underpinning for an extra separate "information risk" factor in an asset-pricing model. For this reason, they suggest that empirical research based on their theory should be directed at the relation between information quality and their market beta.

The second paper addressing asset pricing with imprecise accounting information is the model of Lambert et al. (2012). They derive a noisy rational-expectations model and study the relation between information asymmetry and the cost of equity capital. They show that with perfect competition, information asymmetry is not directly priced but the firm's cost of equity capital is still affected by the average precision of investors' information. However, similar to the result of Lambert et al. (2007), Lambert et al. (2012) conclude that the pricing effect of average precision does not justify a separate information-related risk factor in a pricing model.

Our paper is first to provides a theoretical model that is consistent with empirically modelling both the standard CAPM market premium and market-wide information quality as *separate* priced risk factors in the context of a multiple-regression model.[4] Different from the model of Lambert et al. (2007), our model distinguishes between the standard CAPM (precise) systematic risk (beta) and systematic risk associated with imprecise accounting information. Furthermore, we decompose the firm's total systematic risk into the standard CAPM beta and three additional betas associated with imprecise-information risk.

A related theoretical study by Hughes, Liu, and Liu (2007) examines the impact of *asymmetric information* on asset pricing. The source of information friction in their study comes exclusively from asymmetric information, rather than *information imprecision*. They use an Arbitrage Pricing Theory (APT) framework to derive their model. Their model implies that, at the limit, information asymmetry impacts factor risk

conditionally independent of all other information" (p. 398). Lambert et al.'s (2007) model, as well as our model, presents a structure for the information set, which allows different covariance structures.

[4] This result is in the spirit of multiple-regression models used in the empirical studies of Francis et al. (2004, 2005) Botosan et al. (2004) Aboody et al. (2005) Liu and Wysocki (2006) Core et al. (2008) Ogneva (2008) and Kravet and Shevlin (2010).

premiums, not factor sensitivities. This means that asymmetric-information risk is not priced at the cross section.[5]

In the spirit of Merton (1973), we derive an intertemporal asset-pricing model that examines the pricing of risk associated with imprecise accounting information. We model the impact of imprecise information on asset returns with an Ornstein-Uhlenbeck mean-reverting process under which the information-related return error fluctuates around its long-term mean, to account for reversals in these errors. In the static version of our imprecise-information-adjusted asset-pricing model, information-quality risk has systematic and idiosyncratic components, and only the former is priced. Our model further demonstrates that systematic information-quality risk is priced through three extra asset betas as well as through the alteration of the market risk premium. With an imprecise information set, these three distinct systematic risk effects are measured by covariance (beta) terms between firm-specific and market-wide imprecise-information measures and the precise (fundamental) returns on the asset and the market.

The first component of systematic imprecise-information risk is a function of the covariance of the security's precise return with the information-imprecision return error on the market portfolio. At times when the overall market information-imprecision return error is negative, investors prefer to hold securities that pay a higher precise return. Therefore, investors demand a premium for this covariance. This covariance provides the theoretical underpinning for empirical models testing the cross sectional pricing of the factor loading of an imprecise-information factor (see for example, Francis et al., 2005; Core et al., 2008; Ogneva, 2008; and Kravet and Shevlin, 2010). In this line of empirical literature the imprecise-information factor loading is also related to the covariance of the security return with a market information factor, normally measured by the return on a long-short mimicking portfolio. Thus, we provide further theoretical support for a separate information-quality factor by showing that in equilibrium this market factor exists and the extra risk premium required is distinct from the CAPM market risk premium.

In addition to the above manifestation of systematic risk that has been empirically researched in recent years, our model introduces two novel aspects of theoretically priced

[5] We further discuss Hughes et al. in section 2.1 and 2.4.

systematic imprecise-information risk. First, we have the covariance of the security's imprecise-information return error with the information-imprecision return error on the market portfolio. We call the beta related to this covariance the *commonality in information quality beta*. Assets with a negative commonality covariance provide a hedge against the risk of a negative return due to information imprecision on the market portfolio, and therefore have lower expected returns. Thus, investors expect a higher return premium for a security with a positive commonality in information quality beta.

The second novel form of priced systematic imprecise-information risk in our model is the covariance between the security information-imprecision return error and the market precise return. Here too, investors prefer a negative covariance as it corresponds to higher security information-imprecision return error during a bear market. The implication of this preference is that investors may choose to invest in stocks of firms that erroneously, or even intentionally, release false positive information about the firm at times of a down market. In equilibrium, investors demand a risk premium for stocks that do not provide this hedge due to this covariance term being positive. We provide empirical evidence which strongly supports our theory.

The remainder of this paper is organized as follows: in Section 2 we derive an imprecise-information-adjusted intertemporal asset-pricing model to obtain an analytical asset-pricing framework in the presence of an imprecise-information set. Section 3 discusses the theoretical and empirical implications of imprecise accounting information for asset pricing, while discussing the different channels through which systematic information-imprecision risk affects asset pricing. Empirical evidence in support of our theory is given in Section 4, followed by robustness tests in Section 5. Section 6 provides summary and conclusions.

2. An Intertemporal Asset-Pricing Model with Imprecise Accounting Information

In the current section we formulate a theoretical asset-pricing model with information-quality risk. In particular, we revisit Merton's (1973) intertemporal CAPM by incorporating an imprecise information structure and explore the various channels through which information risk may affect expected asset returns.

We maintain Merton's (1973) assumptions of continuous trading, and that the returns and the changes in the opportunity set (the transition probabilities for returns on each asset over the next trading interval) are well explained by continuous-time stochastic processes. The vector set of stochastic processes describing the investment opportunity set and its changes follow a time-homogeneous Markov process.[6] In the subsection below, we define the imprecise return structure in our model, based on imprecise cash-flow information available to investors. Based on this imprecise return structure, we make two additional assumptions modifying Merton's framework to allow for imperfect information quality.

2.1. The Imprecise Information Set

Merton (1973) describes the equity expected return over a period of length s as:

$$\frac{E[CFPS(t,t+s)]+UCPS(t+s)-P(t)}{P(t)},$$

where $CFPS(t,t+s)$ is cash flow per share generated by a firm between time t and time $t+s$, $UCPS(t+s)$ is the balance of undepreciated capital per share (calculated under physical capital depreciation) held by the firm at time $t + s$, $P(t)$ is the beginning-of-period stock price per share.

Accounting information released by the firm is the principal source of information for estimating the cash flow component of the expected return, and the above definition of expected equity return relies on precise accounting information. Since accounting information is noisy by nature, expected cash-flow estimates, and therefore expected returns, are imprecise. Formally, we follow Lambert et al.'s (2007) definition of the noisy measure of imprecise cash flow as the sum of the firm's precise cash flow per share, $CFPS(t,t+s)$, and an error term that represents the random imprecise cash flow component per share misestimated for the period between time t and time $t + s$,

[6] Merton assumes that all assets have limited liability, and there are no transactions costs, taxes, or problems with indivisibilities of assets. There are a sufficient number of investors with comparable wealth levels so that each investor can buy and sell unlimited amounts at the market prices, and there exists an exchange market for borrowing and lending at the same rate of interest. Investors have homogeneous expectations with respect to asset returns. Short-sales of all assets, with full use of the proceeds are allowed. Finally, it is assumed that trading in assets takes place continually in time. For specific details see Merton (1973).

$\varepsilon(t,t+s)$. This implies the following imprecise expected return on equity over a period s:

$$\frac{E[CFPS(t,t+s)]+E[\varepsilon(t,t+s)]+UCPS(t+s)-P(t)}{P(t)},$$

Given Merton's definition of the precise (fundamental) expected return, the imprecise expected asset return is the sum of the precise expected return and the expected return due to cash flow imprecision:

$$\frac{E[CFPS(t,t+s)]+UCPS(t+s)-P(t)}{P(t)}+\frac{E[\varepsilon(t,t+s)]}{P(t)},$$

We denote the *ex-ante* return due to cash flow imprecision for the period between time t and time $t + s$ with: $\psi(t,t+s)$, such that: $\psi(t,t+s)\equiv\frac{\varepsilon(t,t+s)}{P(t)}$. In the continuous time framework, for an infinitesimally small time interval s, we denote the information-imprecision return error on asset i by ψ_i (for convenience, we drop the time subscript). The inclusion of imprecise accounting information about cash flow leads to the two additional assumptions below, which modify Merton's (precise-information) framework.

Assumption 1: The information-imprecision return error, ψ_i, follows an Ornstein-Uhlenbeck process as follows: $d\psi_i=\kappa(\mu_{\psi_i}-\psi_i)dt+\sigma_{\psi_i}dz_i$, for every asset i (i = 1, 2,…n), where κ, μ_{ψ_i}, σ_{ψ_i} are constants, z_i is standard Wiener process, and $E[dz_i dz_j]=\rho_{\psi_i,\psi_j}dt$, for every asset i (i = 1, 2,…n) and asset j (j = 1, 2,…n).

The drift term $\kappa(\mu_{\psi_i}-\psi_i)$ gives the expected change in the information-related return error. With a positive speed of mean reversion ($\kappa>0$), the level of information-related return error, ψ_i, fluctuates around a long-term steady-state mean, μ_{ψ_i}, which is constant for security i. The parameter σ_{ψ_i} measures the magnitude of the innovation in ψ_i. We assume that the information-related return error follows a mean-reverting process in order to account for reversals in these imprecise-information induced errors.

Assumption 2: Market participants observe the stochastic instantaneous *imprecise* return, $\tilde{r}_i \equiv r_i + \psi_i$, where r_i is the precise return on asset *i*. This precise return follows a Gaussian process: $dr_i = \mu_{r_i} dt + \sigma_{r_i} d\omega_i$, for every asset *i* (*i* = 1, 2,…*n*).

Applying Itô's lemma we write the mean of the instantaneous imprecise return as $\mu_{\tilde{r}_i} = \mu_{r_i} + \mu_{\psi_i}$, which is the sum of the mean instantaneous precise return and the long-term mean of the return error. The instantaneous imprecise return variance is given by: $\sigma^2_{\tilde{r}_i} \equiv \sigma^2_{r_i} + \sigma^2_{\psi_i} + 2\sigma_{r_i,\psi_i}$, where σ_{r_i,ψ_i} is the instantaneous covariance between the precise return on asset *i* and the return due to information imprecision related to asset *i*: $\sigma_{r_i,\psi_i} = \rho_{r_i,\psi_i}\sigma_{r_i}\sigma_{\psi_i}$. The term ρ_{r_i,ψ_i} denotes the instantaneous correlation between the precise return on stock *i* and the information imprecision return errorfor stock *i*.

We further denote the instantaneous correlation coefficient between $d\omega_i$ and $d\omega_j$ (for two different assets *i* and *j*) with ρ_{r_i,r_j}, and the instantaneous correlation coefficient between $d\omega_i$ and dz_j with ρ_{r_i,ψ_j}. That is, $E(d\omega_i d\omega_j) = \rho_{r_i,r_j} dt$ and $E(d\omega_i dz_j) = \rho_{r_i,\psi_j} dt$. The instantaneous covariance between the imprecise returns on any two assets *i* and *j* is given by: $\sigma_{\tilde{r}_i,\tilde{r}_j} = Cov(r_i + \psi_i, r_j + \psi_j) = \sigma_{r_i,r_j} + \sigma_{r_i,\psi_j} + \sigma_{r_j,\psi_i} + \sigma_{\psi_i,\psi_j}$, where σ_{r_i,r_j} is the instantaneous covariance between the precise returns on the two assets.

The above assumptions imply the following Itô processes for the instantaneous imprecise return on the asset *i* ($\tilde{r}_i$):

$$d\tilde{r}_i = (\mu_{r_i} + \kappa(\mu_{\psi_i} - \psi_i))dt + \sqrt{\sigma^2_{r_i} + \sigma^2_{\psi_i} + 2\sigma_{r_i,\psi_i}}\, d\varpi_i\,, \quad (1)$$

where ϖ_i is a standard Brownian Motion.[7] Equation (1) implies that $\{(\mu_{r_i} + \kappa(\mu_{\psi_i} - \psi_i)), \sqrt{\sigma_{r_i}^2 + \sigma_{\psi_i}^2 + 2\sigma_{r_i,\psi_i}}, \rho_{ij}\}$ is a sufficient set of statistics for the *imprecise opportunity set* at any given point in time.

Note that in the current setup all investors face the same imprecise information set. This is similar to the assumption of Lambert et al. (2007) that investors hold homogeneous beliefs about future cash flows (and imprecise return moments in our model), but different from the setup of Lambert et al. (2012) that allows for asymmetric information. In addition, similar to Lambert et al. (2007), our setup facilitates studying the pricing effect of *firm-specific* information imprecision. In Hughes et al. (2007) the information structure is based on the firm's cash-flow component that stems from a factor common to all firms. Different from Lambert et al. (2007) and from the current paper, the idiosyncratic cash-flow portion is cross-sectionally independent in Hughes et al. (2007). Lambert et al. (2007) note that this difference in the information structure leads to different results related to the cross-sectional effects on the expected return on equity. The same difference applies to our model.

2.2. The Investor's Problem

Following Merton (1973), we assume that there are L investors who maximize their expected lifetime utility of wealth given an imprecise information set:

$$J[W(t),\psi(t),t] = \max E_0\left[\int_0^{T_l} U^l[c^l(s),s]ds + B^l[W^l(T^l),\psi(T^l),T^l]\right], \quad l = 1,2,...L, \qquad (2)$$

where "E_0" is the expectation operator, conditional on the current value of the l^{th} investor's wealth and the imprecise information set. U^l is the von Neumann-Morgenstern utility function of consumption for the l^{th} investor, which is strictly concave. The initial value of investor l's wealth is given by $W^l(0) = W^l$. T^l is the l^{th} investor's

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[7] Application of Itô's Lemma implies that: $d\varpi_i = \dfrac{\sigma_{r_i} d\omega_i + \sigma_{\psi_i} dz_i}{\sqrt{\sigma_{r_i}^2 + \sigma_{\psi_i}^2 + 2\sigma_{r_i,\psi_i}}}$, and $E(d\varpi_i dz_i) = \dfrac{\sigma_{r_i}\rho_{r_i,\psi_i} + \sigma_{\psi_i}}{\sqrt{\sigma_{r_i}^2 + \sigma_{\psi_i}^2 + 2\sigma_{r_i,\psi_i}}} dt$.

horizon and $c^l(t)$ is the instantaneous consumption flow at time *t*. Finally, B^l denotes a strictly concave utility function of terminal wealth. The terminal value of lifetime utility in equation (2) is given by: $J[W(T),\psi(T),T]=B(W(T),\psi(T),T)$.

With *n* risky assets and one instantaneously riskless asset, and with imprecise accounting information incorporated in equation (1), the wealth accumulation equation for the l^{th} investor is given by:

$$dW=\sum_{i=1}^{n}q_i W d\tilde{r}_i+(1-\sum_{i=1}^{n}q_i)Wr_f-cdt\,, \tag{3}$$

where q_i is the proportion of the investor's wealth invested in the i^{th} asset. Following Assumptions 1 and 2, the imprecise-information wealth-accumulation process is given by (see derivation in Appendix A):

$$dW=\left[\sum_{i=1}^{n}q_i(\mu_{r_i}+\kappa(\mu_{\psi_i}-\psi_i)-r_f)+r_f\right]Wdt+\sum_{i=1}^{n}q_i W\sqrt{\sigma_{r_i}^2+\sigma_{\psi_i}^2+2\sigma_{r_i,\psi_i}}\,d\varpi_i-cdt,$$

where r_f is an exogenous instantaneous interest rate on a risk-free bond, and $\sum_{i=1}^{n+1}q_i=1$, where q_{n+1} is the weight of the riskless asset. Using the above assumptions and wealth-accumulation process, we solve for an investor's consumption-investment optimal choice which results in the following Hamilton-Jacobi-Bellman (HJB) equation:

$$\begin{aligned}0=\max[&U(c,t)+J_t+J_W[(\textstyle\sum_{i=1}^{n}q_i(\mu_{r_i}+\mu_{\psi_i}-r_f)+r_f)W]\\&+\frac{1}{2}J_{WW}\textstyle\sum_{i=1}^{n}\sum_{j=1}^{n}q_i q_j(\sigma_{r_i,r_j}+\sigma_{\psi_i,\psi_j}+\sigma_{r_i,\psi_j}+\sigma_{r_j,\psi_i})W^2\\&+\frac{1}{2}\textstyle\sum_{i=1}^{n}\sum_{j=1}^{n}J_{\psi_i\psi_j}\sigma_{\psi_i}\sigma_{\psi_j}\rho_{\psi_i,\psi_j}\\&+\textstyle\sum_{i=1}^{n}\sum_{j=1}^{n}J_{W\psi_j}q_i W(\sigma_{r_i,\psi_j}+\sigma_{\psi_i,\psi_j}).\end{aligned} \tag{4}$$

The n+1 first-order conditions for each investor derived from (4) are given by:

$$0=U_c(c,t)-J_W(W,t,\psi), \tag{4.1}$$

$$\begin{aligned}0=&J_W(\mu_{r_i}+\mu_{\psi_i}-r_f)W+J_{WW}\textstyle\sum_{j=1}^{n}q_j W^2(\sigma_{r_i,r_j}+\sigma_{\psi_i,\psi_j}+\sigma_{r_i,\psi_j}+\sigma_{r_j,\psi_i})\\&+\textstyle\sum_{j=1}^{n}J_{W\psi_j}W(\sigma_{r_i,\psi_j}+\sigma_{\psi_i,\psi_j}),\end{aligned} \tag{4.2}$$

$\forall\ i=1,2,\ldots n$ and $j=1,2,\ldots n,$ where $c^*=c(W,t,\psi)$, $q_i^*=q_i(W,t,\psi)$ represent the optimal level of consumption and the optimal weights for assets in portfolio.

2.3. The Optimal Portfolio Choice

The assumption of constant risk-free rate in our model allows us to simplify our analysis and focus on the market for risky equity securities. Using matrix notation, we rewrite equation (4) for the *n* risky assets:

$$0 = J_W(\mu_r + \mu_\psi - r_f I) + J_{WW} W \Sigma_{\tilde{r},\tilde{r}} q + \Sigma_{\tilde{r},\psi} J_{W\psi}, \tag{5}$$

where μ_r is the vector of mean precise returns of the *n* risky securities, μ_ψ is the vector of long-term means of information-imprecision return error (which are also the long-term return spreads between the precise returns and imprecise returns), ψ is the vector of firm-specific information-related return error, $\Sigma_{\tilde{r},\tilde{r}}$ is the variance-covariance matrix of imprecise return vectors $\tilde{r}$ with elements $\sigma_{\tilde{r}_i,\tilde{r}_j} = \sigma_{r_i,r_j} + \sigma_{\psi_i,\psi_j} + \sigma_{r_i,\psi_j} + \sigma_{r_j,\psi_i}$, and $\Sigma_{\tilde{r},\psi}$ is the covariance matrix between the observed imprecise return vector $\tilde{r}$ and the information-related return-error vector ψ on risky assets, with components given by $\sigma_{\tilde{r}_i,\psi_j} = (\sigma_{r_i,\psi_j} + \sigma_{\psi_i,\psi_j})\ \forall\ i = 1,2,...n,$ and $j = 1,2,...n.$ From (5), we obtain the vector of optimal portfolio weights,

$$q^* = -\frac{J_W}{WJ_{WW}} \Sigma_{\tilde{r},\tilde{r}}^{-1}(\mu_r + \mu_\psi - r_f I) - \Sigma_{\tilde{r},\tilde{r}}^{-1} \Sigma_{\tilde{r},\psi} \frac{J_{W\psi}}{WJ_{WW}}. \tag{5.1}$$

We rewrite (5.1) for every asset *i* as follows:

$$q_i^* = -\frac{J_W}{WJ_{WW}} \sum_{j=1}^{n} v_{\tilde{r}_i,\tilde{r}_j} (\mu_{r_j} + \mu_{\psi_j} - r_f I_j) - \sum_{j,k=1}^{n} v_{\tilde{r}_i,\tilde{r}_j} (\sigma_{r_j,\psi_k} + \sigma_{\psi_j,\psi_k}) \frac{J_{W\psi_k}}{WJ_{WW}}, \tag{5.2}$$

$\forall\ i = 1,2,...n,$ $j = 1,2,...n,$ and $k = 1,2,...n.$ $v_{\tilde{r}_i,\tilde{r}_j}$ denotes an element in the inverse of the variance covariance matrix, $\Sigma_{\tilde{r},\tilde{r}}^{-1}$.

Equations (5.1) and (5.2) give the optimal weights (demand) for asset *i* in the presence of imprecise accounting information. The optimal portfolio weight, q^*, in equation (5.1) is the combination of the tangency (market) portfolio with *n* hedge portfolios. This optimal portfolio hedges against imprecise-information risk related to each of the *n* assets, which causes unfavorable changes in the noisy investment opportunity set. Note that, the optimal portfolio composition is altered in the presence of imprecise information not only through the hedge portfolios, but also through the definition of the tangency portfolio, which is altered as well by imprecise return errors.[8]

2.4. The Equilibrium Pricing Equation

The equilibrium asset-pricing equation derived in this section shows that expected asset risk premiums with imprecise accounting information arise due to three elements: (i) the sensitivity of asset returns to the precise excess market return (as in the standard CAPM); (ii) a return sensitivity to a market-wide imprecise information factor; and (iii) the asset return sensitivity with respect to *n* hedge portfolios. The expected excess return on a security takes the following form (see derivation in Appendix B):

$$\mu_{r_i} + \mu_{\psi_i} - r_f = \beta_i^m (\mu_{r_m} - r_f) + \beta_i^m \mu_{\psi_m} + H_i, \qquad (6)$$

where μ_{r_m} is the mean precise market return, $\beta_i^m = \frac{\sigma_{\tilde{r}_i, \tilde{r}_m}}{\sigma_{\tilde{r}_m}^2}$ reflects the i^{th} security return sensitivity to the imprecise-information-adjusted market excess returns, $\tilde{r}_m$ is the imprecise return on the market portfolio, $\tilde{r}_m = \sum_{i=1}^n x_i \tilde{r}_i$. In the intertemporal model, investors hold *n* hedge portfolios, represented by a vector *h*, to hedge against the fluctuations in imprecise returns that cause random shifts in the imprecise information set. This result implies the following extra term in equation (6): $H_i = \sum_{k=1}^n \sum_{j=1}^n (\beta_i^m \sigma_{\tilde{r}_m, \psi_j} - \sigma_{\tilde{r}_i, \psi_j}) b_{\tilde{r}_{h,j}, \tilde{r}_{h,k}} (\pi_k^h - \beta_k^h \pi^m)$ that represents the risk premium associated with the *n* hedge portfolios. The term: $\pi^m = (\mu_{r_m} - r_f) + \mu_{\psi_m}$ is the market risk premium adjusted for imprecise accounting information, $\beta_k^h = \frac{\sigma_{\tilde{r}_{h,k}, \tilde{r}_m}}{\sigma_{\tilde{r}_m}^2}$ is the k^{th} hedge portfolio's return sensitivity to imprecise-information-adjusted excess market returns, $\tilde{r}_{h,k}$ is the imprecise return on hedge portfolio *k*, $\pi_k^h = (\mu_{r_{h,k}} - r_f) + \mu_{\psi_{h,k}}$ is the imprecise information adjusted risk premium on the k^{th} hedge portfolio, and $b_{\tilde{r}_{h,j}, \tilde{r}_{h,k}}$ denotes an element in the inverse matrix $\Gamma_{\tilde{r}_h}^{-1}$, which is presented in Appendix B.

[8] The optimal portfolio choice varies across investors as reflected in the different derivatives of the investor's expected lifetime utility of wealth, *J*.

Equation (6) is the equilibrium intertemporal capital asset pricing equation with information imprecision. It describes the equilibrium relation between the asset risk premium and three types of risk: market (systematic) risk, systematic information imprecision risk, and the risk of unfavorable shifts in the stochastic investment opportunity set. Equation (6) further shows that imprecise accounting information affects the risk premium associated with the asset betas (risks). In addition to the standard CAPM market risk premium, $(\mu_{r_m} - r_f)$, investors also demand a premium for asset return sensitivity to the market-wide information-quality risk factor, μ_{ψ_m}.

Systematic risk is measured by the sensitivities (betas) with respect to the market portfolio, information-quality factor, and the hedge portfolios. The imprecise-information related adjustment in β_i^m and β_k^h highlights a significant difference from the APT model of Hughes et al.'s (2007). In their model, risk related to asymmetric information only affects factor risk premiums, not factor sensitivities. Unique to our model, the risk associated with the imperfect-information attribute we consider (information imprecision) affects the risk premiums as well as factor sensitivities. As a result, information imprecision is systematic and cross-sectionally priced. We further explore this point and explain the way in which imprecise accounting information alters factor sensitivities in Section 3.

3. Empirical and Theoretical Implications of Imprecise Accounting Information

In this section, we further analyze the implications of our model using a more tractable static version of equation (6). To arrive at the static version, we assume that every k^{th} hedge portfolio is correctly priced by its return sensitivity to the noisy market factor (in other words, $H_k = 0$, for every k).[9] Under this assumption we can write equation (6) as follows for every k^{th} hedge portfolio:

$$\mu_{r_{h,k}} + \mu_{\psi_{h,k}} - r_f = \beta_k^m(\mu_{r_m} - r_f) + \beta_k^m \mu_{\psi_m}.$$

[9] Alternative to this assumption, there are two additional assumptions that lead to the static version of our model in equation (7). First, one can assume the derived utility function, J, is either additive in wealth and return errors. Second, imprecise returns have a factor structure.

With the notations used following the discussion of equation (6), this is equivalent to: $\pi_k^h = \beta_k^h \pi^m$ for every k.[10] Thus the pricing error on hedge portfolio return, represented by $(\pi_k^h - \beta_k^h \pi^m)$, becomes zero. This implies that: $H_i = \sum_{k=1}^n \sum_{j=1}^n (\beta_i^m \sigma_{\tilde{r}_m,\psi_j} - \sigma_{\tilde{r}_i,\psi_j}) b_{\tilde{r}_{h,j},\tilde{r}_{h,k}} (\pi_k^h - \beta_k^h \pi^m) = 0$ for every asset i, which leads to the static version of our imprecise-information-adjusted asset-pricing model:

$$\mu_i + \mu_{\psi_i} - r_f = \beta_i^m (\mu_{r_m} - r_f) + \beta_i^m \mu_{\psi_m}, \tag{7}$$

where: $\beta_i^m = \frac{\sigma_{\tilde{r}_i,\tilde{r}_m}}{\sigma_{\tilde{r}_m}^2} = \frac{\sigma_{r_i,r_m} + \sigma_{r_i,\psi_m} + \sigma_{\psi_i,\psi_m} + \sigma_{\psi_i,r_m}}{\sigma_{r_m}^2 + \sigma_{\psi_m}^2 + 2\sigma_{r_m,\psi_m}}$ and $\sigma_{\tilde{r}_m}^2 = \sigma_{r_m}^2 + \sigma_{\psi_m}^2 + 2\sigma_{r_m,\psi_m}$. The ensuing discussion is based on this static version.

3.1. Empirical Implications of the Imprecise-Information-Adjusted CAPM

Equation (7) provides the theoretical underpinning for incorporating an information-imprecision risk factor in a regression model as a separate market factor. Recall that Lambert et al. (2007) do not provide a theoretical justification for the pricing of an information-quality factor. In their one-period CAPM-based model, the cross-sectional pricing of imprecise information manifests through the estimation of the firm's cash-flow beta. They emphasize that their model does not provide the theoretical foundation for an extra separate "information risk" factor in an asset-pricing model. However, our imprecise-information-adjusted model provides a pricing relation that is consistent with empirically modeling both market-wide information-quality risk premium(μ_{ψ_m}) and the standard CAPM market risk premium ($\mu_{r_m} - r_f$) as *separate* priced risk factors in the context of a multiple-regression model (as in the empirical work of Francis et al., 2004, 2005; Botosan et al. (2004); Aboody et al. (2005); Liu and Wysocki (2006); Core et al., 2008; Ogneva, 2008; and Kravet and Shevlin,). In addition, in our model imprecise accounting information also affects asset prices cross-sectionally through its impact on the firm's imprecise-return beta (rather than the Lambert et al. cash-flow beta).

In the next subsection, we decompose our imprecise-return beta and investigate

[10] Note that, β_k^m and β_k^h refer to the same thing: hedge portfolios' return sensitivities to market excess returns.

the three different channels through which imprecise information is manifested as a systematic risk factor in our model, two of which are unique to this paper. We further show that one of these channels is closely related to the factor loading of the information-quality factor that appears in the above body of empirical work. This provides further theoretical support for empirically modeling a distinct information-quality factor.

3.2. Theoretical Implications of the Imprecise-Information-Adjusted CAPM

Under the static version of the imprecise-information-adjusted CAPM given in equation (7), the three-fund separation of the intertemporal model collapses to the standard equation that reflects a two-fund separation in the static CAPM, adjusted for imprecise accounting information. The two mutual funds (the riskless asset and the market portfolio) allow the investor to create a risk-return profile comparable to that of asset *i* on an instantaneously efficient frontier. Thus, the imprecise-return beta in equation (7) measures the risk contribution of asset *i* ($\sigma_{\tilde{r}_i,\tilde{r}_m}$) to the total risk of holding the market portfolio ($\sigma^2_{\tilde{r}_m}$), which consists of a systematic component of imprecise-information risk.

After expanding the covariance term in equation (7) we can write the asset pricing equation as follows:

$$\mu_{r_i} + \mu_{\psi_i} = r_f + \pi^m \frac{\sigma_{r_i,r_m}}{\sigma^2_{\tilde{r}_m}} + \pi^m \frac{\sigma_{r_i,\psi_m}}{\sigma^2_{\tilde{r}_m}} + \pi^m \frac{\sigma_{\psi_i,\psi_m}}{\sigma^2_{\tilde{r}_m}} + \pi^m \frac{\sigma_{\psi_i,r_m}}{\sigma^2_{\tilde{r}_m}}. \tag{8}$$

Recall that $\pi^m = (\mu_{r_m} - r_f) + \mu_{\psi_m}$, is the imprecise-information-adjusted risk premium on the market. The long-term equilibrium imprecise-information-adjusted asset-pricing model in Equation (8), provides the framework for understanding the various channels through which imprecise-information risk may affect asset returns.

Unlike the model of Lambert et al. (2007), our model distinguishes between the standard CAPM (precise) systematic risk and systematic risk associated with imprecise information. This is reflected in equation (8) where we decompose the firm's total systematic risk into the standard CAPM beta and three additional betas associated with imprecise-information risk. These four betas are related to the following covariance terms: $\sigma_{r_i,r_m}, \sigma_{r_i,\psi_m}, \sigma_{\psi_i,\psi_m}$, and σ_{r_m,ψ_i}. The first term, σ_{r_i,r_m}, is the standard CAPM covariance of the precise returns on the individual asset (r_i) and on the market (r_m). With an imprecise information set the three distinct betas representing systematic information-quality risk are related to the following covariance terms: σ_{r_i,ψ_m}, σ_{ψ_i,ψ_m}, and σ_{r_m,ψ_i}. Below, we show that the first covariance term captures the effect of the information-quality factor of Francis et al. (2005). The other two covariance terms reveal two novel channels that manifest the pricing of systematic risk related to information imprecision.

The first systematic imprecise-information risk term, σ_{r_i,ψ_m}, is the covariance between the security's precise return (r_i) and the overall market imprecise-information return error (ψ_m). In the CAPM world investors hold the market portfolio. Investors prefer securities for which this covariance has a negative sign so that the security tends to pay a positive precise return at times when the market portfolio suffers from a negative imprecise-information return error.[11] Stated differently, when this covariance is negative, the security hedges against market losses due to information imprecision. This means that investors demand a risk premium when this covariance term is positive. Therefore, this covariance term provides the theoretical framework for the cross-sectional *pricing* of the Francis et al. (2005) information-quality factor loading, which is a function of σ_{r_i,ψ_m}. Note that the two remaining betas (covariance terms) represent two new channels that are unique to our model, through which systematic imprecise-information risk affects asset prices.

The second imprecise-information beta is related to the term σ_{ψ_i,ψ_m}, which is the covariance between the security's information-related return (ψ_i) and the overall market imprecise-information return error (ψ_m). Investors holding the market portfolio prefer securities for which this covariance is negative so that the security tends to pay a positive imprecise-information return error at times when the market portfolio suffers from a negative imprecise-information return error. In other words, when this covariance is negative, the favorable imprecise accounting information about this security hedges against market losses due to information imprecision. We call the beta related to this covariance ($\sigma_{\psi_i,\psi_m} / \sigma^2_{\tilde{r}_m}$) the *commonality in information quality beta*. Investors will

[11] The analysis in this paper assumes that the market risk premium, π^m, is positive, which is empirically consistent.

demand a risk premium for securities with a positive commonality in information quality beta.

The last component of systematic risk related to imprecise information, σ_{ψ_i, r_m}, is the covariance between the security's return due to information imprecision (ψ_i) and the overall market precise return (r_m). In this case, investors prefer to hold securities that hedge with a positive imprecise-information return error against a bearish market. This means that investors holding the market portfolio prefer securities for which this covariance is also negative, so that the security tends to pay a positive imprecise-information return error at times when the market portfolio suffers from a negative precise return. This implies that – for portfolio hedging purposes – investors may prefer to invest in stocks of firm's that erroneously, or even deliberately, release false positive information about the firm at times of a down market. Here again, investors demand a risk premium when this last covariance term is positive.

Finally, two-fund separation implies that investors hold the market portfolio. In our model, the risk involved in holding the market when information is imprecise is given by: $\sigma^2_{\tilde{r}_m} = \sigma^2_{r_m} + \sigma^2_{\psi_m} + 2\sigma_{r_m, \psi_m}$. This means that the total systematic risk consists of three components: the precise market-portfolio risk ($\sigma^2_{r_m}$), risk related to imprecise-information market return ($\sigma^2_{\psi_m}$), and the comovement of market precise return and imprecise-information market return (σ_{r_m, ψ_m}). Therefore, the presence of $\sigma^2_{\psi_m}$ and σ_{r_m, ψ_m} shows explicitly that imprecise-information risk cannot be diversified away, even in the context of a very large portfolio such as the market portfolio.

The above discussion highlights that our static version of the imprecise-information-adjusted asset-pricing model presents three distinct channels through which this systematic imprecise-information risk is priced. Equation (8) implies that investors demand a higher risk premium due to the three additional information-related betas representing systematic imprecise-information risk they face. This risk is priced because, even when one holds security *i* within a large portfolio such as the market portfolio, one still faces the systematic information-quality risk that security *i* contributes to the market portfolio. Unique to our model, this risk is priced through an altered market risk premium as well as through the factor loadings of the security. In the next section we provide empirical evidence in support of our static model.

4. Empirical Evidence

In this section we test the empirical validity of an unconditional version of our static asset-pricing model. Mechanically, our model is somewhat similar to the liquidity-adjusted CAPM of Acharya and Pedersen (2005), but the focus of our model is clearly different. Contextually, Acharya and Pedersen (2005) derive an overlapping-generations model accounting for liquidity risk, while our model is an intertemporal model considering information-quality risk. Analytically, although both models are four-beta models, the signs of the betas in the pricing equation are different. The similarities however enable us to follow an empirical testing procedure in the spirit of Acharya and Pedersen (2005).

We assume constant conditional covariances of innovations in information-imprecision return errors and returns and derive the following unconditional version of our static model based on equation (8)[12]:

$$\mu_{\tilde{r}_{it}} - r_{ft} = \pi_t \beta_i^{Market} + \pi_t \beta_i^{IQ,1} + \pi_t \beta_i^{IQ,2} + \pi_t \beta_i^{IQ,3}, \tag{9}$$

where

$$\beta_i^{Market} = \frac{Cov(r_{it}, r_{mt} - E_{t-1}(r_{mt}))}{Var(r_{mt} - E_{t-1}(r_{mt}) + [\psi_{mt} - E_{t-1}(\psi_{mt})])},$$

$$\beta_i^{IQ,1} = \frac{Cov(r_{it}, \psi_{mt} - E_{t-1}(\psi_{mt}))}{Var(r_{mt} - E_{t-1}(r_{mt}) + [\psi_{mt} - E_{t-1}(\psi_{mt})])},$$

$$\beta_i^{IQ,2} = \frac{Cov(\psi_{it} - E_{t-1}(\psi_{it}), \psi_{mt} - E_{t-1}(\psi_{mt}))}{Var(r_{mt} - E_{t-1}(r_{mt}) + [\psi_{mt} - E_{t-1}(\psi_{mt})])},$$

$$\beta_i^{IQ,3} = \frac{Cov(\psi_{it} - E_{t-1}(\psi_{it}), r_{mt} - E_{t-1}(r_{mt}))}{Var(r_{mt} - E_{t-1}(r_{mt}) + [\psi_{mt} - E_{t-1}(\psi_{mt})])},$$

$\pi_t = (\mu_{r_{mt}} - r_{ft}) + \mu_{\psi_{mt}} = \mu_{\tilde{r}_{mt}} - r_{ft}$, and $\mu_{\tilde{r}_{iit}} = \mu_{r_{it}} + \mu_{\psi_{it}}$. This unconditional static version of our model is the basis the empirical test to follow.

[12] The unconditional version of our model can be derived under an alternative assumption that dividends and information-imprecision return errors are independent over time. However, we cannot adopt this alternative assumption because empirically our information-imprecision return error proxy is persistent.

4.1 Data and Methodology

We use monthly stock prices, returns, and market capitalization data from CRSP for NYSE, Amex, and Nasdaq stocks for the period between January 1970 and December 2010. Consistent with previous literature, we include only US common stocks (CRSP codes of 10 or 11). The accounting data are from the Compustat database. Each month we exclude penny stocks and stocks with price greater than $1000 based on beginning-of-month prices. We further exclude size outliers, defined as observations with market capitalization within the upper and lower 2.5 percentiles of our sample.[13]

4.2 Measuring the Information-Imprecision Return Error

To estimate equation (9), we need a proxy for the information-imprecision return error, ψ_{it}. A significant body of research in accounting and finance suggests measures of accrual quality to proxy for firm information quality (see for example, Barth et al., 2001; Dechow and Dichev, 2002; McNichols, 2002; Francis et al., 2005; Core et al., 2008, and Lee and Masulis, 2009). The premise of this interpretation of accrual quality is that cash flow is the primitive element for pricing, and therefore poor accrual quality is a cause for weaker mapping between cash flow and price and thus an indication of feeble information quality.

We adopt the modified Dechow and Dichev (DD hereafter, 2002) model and estimate an accruals-quality (or information-quality) measure as proxy for the information-imprecision return error, ψ_{it}. DD model current accruals as a function of current, past, and future cash flows. This approach views the primary role of the matching function of accruals to cash flows in determining accrual quality. The intuition

[13] The estimation of the information-imprecision return error proxy we use below requires companies in our sample to have survived for at least four years prior to the estimation year. As a result, the sample is systematically biased towards older, larger, and more successful firms, while it excludes recently-listed (younger) firms and firms delisted over this sample period (see Core et al., 2008; and Lee and Masulis, 2009). Since older and larger firms are more likely to have higher information quality, the removal of firms with market capitalization within the top 2.5 percentile addresses the structural sample bias towards larger firms. At the same time, smaller-size and younger firms are more likely to suffer from poor information quality, hence are more likely to agree with the implications of our model. Therefore, to avoid this potential bias in favor of our model, we also remove firms with market capitalization within the bottom 2.5 percentile.

behind this measure is that managers have some discretion over the timing or cash flow recognition across adjacent accounting periods.[14] DD suggest that estimation errors in accruals and their subsequent corrections are likely to reduce the beneficial role of accruals, thus the quality of accruals is decreasing in the magnitude of accrual estimation errors. In addition to cash flows, we augment changes in sales revenue and property, plant, and equipment because these components are important in forming expectations about current accruals, beyond their direct effects on operating cash flows (see McNichols, 2002).[15] The modified DD model is specified as:

$$TCA_{i,t} = \phi_0 + \phi_1 CFO_{i,t-1} + \phi_2 CFO_{i,t} + \phi_3 CFO_{i,t+1} + \phi_4 \Delta \mathrm{Rev}_{i,t} + \phi_5 PPE_{i,t} + e_{i,t}, \tag{10}$$

where

$TCA =$ total current accruals = $(\Delta CA - \Delta Cash) - (\Delta CL - \Delta STDEBT)$,

ΔCA = change in current assets,

$\Delta Cash$ = change in cash/cash equivalents,

ΔCL = change in current liabilities,

$\Delta STDEBT$ = change in short-term debt,

Dep = depreciation and amortization expenses,

CFO = cash flow from operation= $NIBE - (TCA - Dep)$,

$NIBE$ = net income before extraordinary items,

ΔRev = change in revenue, and

PPE = gross property, plant, and equipment.

All variables are drawn from the yearly Computstat database and are scaled by the average of total assets between year *t*-1 and year *t*. We estimate Equation (10) at the cross-section for every year within each industry with at least 20 observations in a given

[14] This is because accruals anticipate future cash collections or payments and reverse when previously recognized cash in accruals is received or paid. As a result, the timing of a firm's economic accomplishments and sacrifices often differs from the timing of their related cash flows. Managers can benefit from this disparity when they use accruals to adjust cash flow timing, but it comes with a cost, namely, an offsetting change in next period's accruals and earnings. For example, recording a receivable accelerates the recognition of a future cash flow in earnings and matches the timing of the accounting recognition with the timing of the economic benefits from the sale. However, if net proceeds from a receivable are less than the original estimate, then a subsequent entry records both the cash collected and the correction of the estimation error.

[15] McNichols shows that adding these two variables significantly increases the model's explanatory power in the cross-sectional regression, thus reducing measurement error.

year, based on two-digit Standard Industrial Classification (SIC) industry groups.[16] We exclude financial institution, insurance, and real estate companies (SIC codes 6000-6999).

Recall that in section 2.1 we define the information-imprecision component of return as the random misestimated cash-flow component per share, scaled by the share price so that it takes the form of a rate of return. Since all variables in the DD regression model are scaled by total assets, the DD regression residual, $e_{i,t}$, is also a rate of return (albeit relative to the firm's assets rather than its market value) representing accrual-related errors in estimating cash flows. Thus, the raw cash-flow regression residual is the most natural proxy for our information-quality return error (ψ_{it}). Note that the DD regression residual term, could be negative or positive, and as a regression error term is white noise. To insure that its effect is not lost at the aggregate, our firm-year proxy for the information-quality return error is given by: $IQ = \hat{\psi}_{it} \,|\, e_{i,t} \,|$, which is the absolute value of the estimated residual of the DD model. This measure was first suggested by DD (see footnote 6 in DD).

Note that a more popular accrual-quality measure is given by the standard deviation of firm's annual DD regression residuals across time (see for example, Dechow and Dichev, 2002; McNichols, 2002; Francis et al., 2005; Core et al., 2008, and Lee and Masulis, 2009). However, this standard deviation measure is used in the extant literature to proxy for the *accrual quality* (or *quality of information*) of the firm, rather than to proxy for *information-quality return error*. Since the latter is an input of our model, the absolute value of the DD model residual (*IQ*) is a more valid proxy for the testing of our model's validity.

For the purpose of measuring information quality (rather than measuring our information-quality return error), the standard deviation of the firm's DD regression residuals is a superior measure. This is because one may consider a firm with a zero mean of $|e_{i,t}|$ as a sign of perfect information quality. However, if $|e_{i,t}|$ exhibits great variability (even with a zero mean), then in actuality the firm has poor information quality. At the same time, when using $|e_{i,t}|$ we must maintain the assumption that its

[16] When there are less than 20 observations, we estimate the model based on one-digit SIC.

standard deviation is positive. Otherwise, a positive but deterministic $|e_{i,t}|$ implies that all three information-quality betas in our model take a zero value. Given the noisy nature of regression residuals, this assumption about our *IQ* proxy clearly holds empirically.[17]

Our *IQ* proxy is estimated with balance-sheet and income-statement information rather than statement of cash flows information. Given evidence suggesting that balance-sheet accruals estimates are potentially biased (see Hribar and Collins, 2002), we repeat our tests with an alternative cash-flow statement based *IQ* proxy. However, for an asset-pricing test, the increased accuracy resulting from using cash-flow statement data (with data starting in 1988), comes at a great cost of a significantly shorter sample period relative to the *IQ* proxy measured with information from the balance sheet and income statement (with data starting in 1970). Consequently, we focus our discussion on balance-sheet *IQ* proxy based tests. We report our results for the cash-flow statement *IQ*-based tests with the robustness tests findings below.

4.3 Creating Test Portfolios and a Market Portfolio

To reduce noise related to the individual stock estimated information-precision return error proxy, we form 25 test portfolios based on the previous year *IQ* proxy estimated for each individual stock. Portfolio return and portfolio *IQ* measure are calculated both as equal- and value-weighted averages for each of the 25 test portfolios. These averages are calculated for each month in our sample period over stocks that are included in a given portfolio. We construct value-weighted and equal-weighted test portfolios. The DD estimation of our *IQ* measure requires four consecutive years of data that include: the estimation year, two years prior to the estimation year (since lagged *CFO* is a first-difference variables), and one year after the estimation year. The *IQ* estimation is based on data from January 1970 to December 2010. Since our test portfolios are formed based on the previous-year *IQ* proxy, we obtain monthly test-portfolio *IQ* measures and returns for the January 1973 to December 2010 (38-year) period.

[17] Given the wide use of the standard deviation of firm's annual DD regression residuals as a measure for accrual-quality, we repeat our tests with this popular (albeit less suitable) alternative proxy. These findings are reported with the results of the robustness tests below.

The market portfolio in our model is a value-weighted portfolio of all risky assets in the economy. However, our sample is limited to stocks reported on CRSP and listed on the NYSE, Amex, and Nasdaq. This means that we exclude other risky assets, such private equity, small-firm stocks, different forms of corporate debt, and real estate.[18] This set of omitted assets is dominated by low information quality assets. In addition, recall that the data requirements of the *IQ* measure estimation procedure systematically excludes younger firms and firms delisted over our sample period – both types tend to have low information quality. As a result, our universe is biased towards stocks issued by larger and stronger firms with high quality information. For this reason, in the spirit of Acharya and Pedersen (2005), we counterbalance the over-representation of these high information-quality stocks in our sample by calculating equal-weighted averages of market portfolio return and market portfolio *IQ* measure,). These market portfolio averages are calculated for each month in our sample period over stocks that are included in our sample with a previous-year *IQ* measure. For robustness, below we also repeat results for tests with a value-weighted market portfolio.

4.4 Beta Estimation and Evidence of Imprecise-information Risk in Pricing

Since our *IQ* measure is time varying and persistent, we focus on the unconditional model in equation (9), in which the beta estimation involves estimating four sets of innovations: (*i*), market portfolio return innovations; (*ii*), market portfolio *IQ* proxy innovations; (*iii*), *IQ* proxy innovations for each portfolio; and (*iv*), portfolio return innovations. We find that an AR(1) or an AR(2) specification is most suitable for removing serial correlations and to estimate innovations in the 25 test-portfolio *IQ* measures and in the market portfolio *IQ* measure. Since the AR(2) specification is a better fit for most portfolios, innovations in portfolio returns are estimated using this specification with the portfolio *IQ* measure as a control variable. Market portfolio return innovations are also computed using an AR(2) model, adjusted for market characteristics at the beginning of each month, which include: market volatility, log of one-month

[18] According to Heaton and Lucas (2000) asset-class proportions of national wealth are allocated as follows: private equity corresponds to 13.8%, other financial wealth is 28.2%, real estate (owner-occupied) represents 33.3%, and consumer durables correspond to 11.1%. At the same time, stocks represent only 13.6% of national wealth.

lagged market capitalization, lagged book-to-market ratio, average of previous six month turnover, the average of previous six months illiquidity reflected by the Amihud (2002) measure, and the average of previous six months *IQ* measure.

Based on the four sets of innovations, we estimate four betas for each of the 25 test portfolios: $\beta_p^{Market}, \beta_p^{IQ,1}, \beta_p^{IQ,2}$, and $\beta_p^{IQ,3}$. We then use alternative cross-sectional specifications of the model to identify the potential effect of information-quality systematic risk in total, and the effect of each information-quality beta separately. The first specification constraints the beta risk premium to be identical for all four betas:

$$E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi\beta_p^{All}, \qquad p=1,2,..25, \tag{9.1}$$

where $\tilde{r}_{pt} = r_{pt} + \hat{\psi}_{pt}$ representing the observed portfolio return, and $\beta_p^{All} = \beta_p^{Market} + \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$ representing the overall (market and information-quality) systematic risk in the portfolio.

To disentangle information-quality risk (at the aggregate) from the standard CAPM market risk we test our second specification as follows:

$$E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ}\beta_p^{IQ}, \qquad p=1,2,..25, \tag{9.2}$$

The first beta, β^{Market}, in model specification (9.2) is the standard CAPM beta reflecting the portfolio return sensitivity relative to the market portfolio return. The second beta, $\beta_p^{IQ} = \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$ represents the portfolio systematic information-quality risk at the aggregate.

To compare the effects of the different dimensions of systematic information-quality risk on return, we decompose the aggregate information-quality beta into three betas: $\beta_p^{IQ,1}, \beta_p^{IQ,2}$, and $\beta_p^{IQ,3}$, as specified in equation (9). Thus, we allow for a unique risk premium for each beta in the following equation:

$$E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ,1}\beta_p^{IQ} + \pi^{IQ,2}\beta_p^{IQ,2} + \pi^{IQ,3}\beta_p^{IQ,3}, \quad p=1,2,..25, \tag{9.3}$$

Regression model (9.3) represents the unconditional version of our static model with the four betas spelled out. Recall that there are three different channels through which imprecise information is manifested as a systematic risk factor in our model. The first channel is represented by $\beta_p^{IQ,1}$, reflecting the sensitivity of portfolio return relative to market-wide imprecise-information return error. The second information-quality risk component, $\beta_p^{IQ,2}$, is the commonality in information quality beta, reflecting the co-movement between individual portfolio information-imprecision return error and that of the market. The last information-imprecision risk channel, β_3^{IQ}, represents the association between the portfolio information-quality return error and the market return.

Empirically, estimating regression model (9.3) is problematic due to the high multicollinearity between the three information-quality risk betas. This is documented in the correlation matrix reported in Table A.1 in the appendix. While for the sake of exposition we still report the estimated coefficient for regression model (9.3), we caution against their interpretation. Note that multicollinearity is not an issue in regression models (9.1) and (9.2).

4.5 Results

We apply GMM to estimate regression models (9.1) – (9.3) cross sectionally over our 25 (value- and equal-weighted) test portfolios using our *IQ* proxy. We also estimate a single beta model with each of the four betas from equation (9). Table 1 documents the GMM coefficient estimates for test based on an equal-weighted market portfolio. Panel A reports results for the 25 *IQ*-sorted value-weighted portfolios. The estimation of regression model (9.1), with a single risk premium for the sum of all four betas, β_p^{All}, yields a risk premium for our information-quality adjusted model that is positive and significant at a 1% level. In addition, the R^2 of our model is relatively high (0.554) when compared with that of the standard CAPM (0.455).

Table 1 Here

Recall that regression model (9.2) allows us to disentangle the impact of systematic information-quality risk from that of the standard CAPM systematic market risk. For the value-weighted portfolios, Panel A further reports that the aggregate systematic information-quality risk, β_p^{IQ}, has an estimated risk premium that is positive and significant at a 1% level. At the same time, the standard market risk premium in this specification (the market beta coefficient) is still significant, but only at a 5% level (compared with a 1% significance under the standard CAPM regression).

When comparing the results for the four single beta regression models, we see that the estimated coefficient is significant at the 1% level for all four betas. However, it seems like the $\beta_p^{IQ,3}$ model (related to the covariation of portfolio information-quality return error with the market return) has the highest explanatory power for the cross-sectional variation in portfolio returns (R^2) among the four single-beta models.

While the estimated coefficients of all three information-quality betas in regression model (9.3) are statistically significant, recall that these are not interpretable due to the high multicollinearity exhibited for the three estimated betas. This is supported by the R^2 of this specification which is by far the highest of all reported regression models (0.709).

In general, the results for the 25 *IQ*-sorted equal-weighted portfolios (reported in Panel B of Table 1) are consistent with those reported for the value-weighted portfolios. The main difference is that for equal-weighted portfolios regression model (9.2) yields an insignificant risk premium for the standard market risk, while the information-quality risk remains significant at the 1% level.

Overall, the evidence presented in Table 1 (for tests based on an equal-weighted market portfolio), lends strong support for the unconditional version of our information-quality adjusted asset-pricing model. This is reflected by significant estimated coefficients for β_p^{All} and β_p^{IQ} with high regression R^2's in regression models (9.1) and (9.2), respectively, indicating that our model fits the data well.

5. Further Investigations

Below we report the results of four additional robustness tests to assess the empirical performance of our model. First, we report results for tests conducted with a value-weighted market portfolio. Second, given the wide use of the standard deviation of firm's annual DD regression residuals as a measure for accrual-quality, we report results of tests using this popular alternative proxy. Third, we report results for the cash-flow statement IQ-based tests. Finally, we test whether the pricing of our systematic information-quality risk is robust when one considers Acharya and Pedersen (2005) systematic liquidity risk. With the exception of the first test, the results for the remaining three tests are reported for value-weighted test portfolios with an equal-weighted market portfolio.

5.1 Tests Utilizing a Value-Weighted Market Portfolio

Recall that we follow Acharya and Pedersen (2005) and calculate equal-weighted averages of market portfolio return and market portfolio *IQ* measure in our tests. We do this to counterbalance the over-representation of relatively large and high information-quality stocks in our CRSP sample. However, theoretically the market portfolio in our model is a value-weighted portfolio of all risky assets in the economy. Table 2 reports the GMM coefficient estimates for test based on a value-weighted market portfolio. Panel A documents results for the 25 *IQ*-sorted value-weighted portfolios. For regression model (9.1), with a single risk premium estimated for the sum of all four betas, β_p^{All}, the risk premium for our information-quality adjusted model is positive and significant at a 1% level. Also, the R^2 of our model is much higher (0.576) than that of the standard CAPM (0.281).

Table 2 Here

Panel A further reports the results of regression model (9.2) which disentangles the impact of systematic information-quality risk from that of the standard CAPM systematic market risk. For the value-weighted portfolios, we find that the aggregate systematic information-quality risk, β_p^{IQ}, has an estimated risk premium that is positive and significant at a 1% level. At the same time, the standard market beta coefficient is still significant, but only at a 5% level (compared with a 1% significance under the standard CAPM regression).

Moving on to the results for the four single beta regression models, we find that the estimated coefficient is significant at the 1% level for all four betas. Similar to the results reported for the equal-weighted market portfolio case, the $\beta_p^{IQ,3}$ model has the highest R^2 among the four single-beta models. We again find that the R^2 of regression model (9.3) is the highest among all other specification (0.612). This is combined with the result that the only significant coefficient is that of $\beta_p^{IQ,3}$ with a 5% significance level. The regression coefficients of all other three betas are now insignificant. These results are once again an artifact the multicollinearity exhibited for the three estimated betas.

Once again, the results reported in Panel B of Table 2 for the 25 *IQ*-sorted equal-weighted portfolios are consistent with those reported for the value-weighted portfolios. Overall, the evidence for tests based on a value-weighted market portfolio presented in Table 2, provide strong support for the unconditional version of model. Hence, the support for our model is robust with respect to whether we use equal- or value-weighted market portfolio in our tests. In addition, our conclusion is also insensitive to whether we use equal- or value-weighted test portfolios. Therefore, the remainder of the robustness tests are conducted with an equal-weighted market portfolio (following Acharya and Pedersen, 2005) and with value-weighted tests portfolios (consistent with our theoretical model).

5.2 Using an Alternative IQ proxy

Because of the popularity of the standard deviation of the DD regression residuals in research focusing on accrual (or information) quality, we repeat our tests with this proxy for robustness. The results of tests utilizing this proxy will indicate the soundness of the general idea in our model, that the information-quality effect is manifested in priced systematic risk. However, as previously mentioned, tests using the absolute value of the estimated residual of the DD model as the *IQ* proxy provide more direct evidence with respect to the empirical validity of our model. Our alternative proxy is given by the standard deviation of firm *i*'s cross-sectional regression residuals across five years:

$IQ' = \sigma(e_{i_t}, e_{i_{t-1}}, e_{i_{t-2}}, e_{i_{t-3}}, e_{i_{t-4}})$. We estimated this proxy using balance sheet data. This alternative proxy reflects the stability dimension of information quality, implying that larger IQ' represents a lower predictability of earnings and therefore a lower quality of financial reporting.[19]

Turning to a practical matter, when estimating the standard-deviation proxy based on the DD model using annual accounting data, we need eight consecutive years with financial accounting data, implying that companies have survived for at least six years prior to the estimation year.[20] Consequently, the sample for estimating the standard-deviation *IQ* proxy is even more biased than that of the absolute-value *IQ* proxy which requires four years of consecutive data. Recall that this bias systematically excludes recently-listed (younger) firms and firms delisted over this sample period, while it is biased towards older, larger, and more successful firms which tend to have higher quality of information (see Core et al., 2008; and Lee and Masulis, 2009).

Table 3 documents the GMM coefficient estimates for test based on an equal-weighted market portfolio and IQ'-sorted value-weighted portfolios. Once again, the estimated risk premium in regression model (9.1) is positive and significant at a 1% level. In addition, the R^2 of this model (0.224) is almost double that of the standard CAPM (0.144).

Table 3 Here

For regression model (9.2), which separates systematic information-quality risk from that of the standard CAPM systematic market risk, the estimated risk premium for the aggregate systematic information-quality risk is positive and significant at a 5% level. At the same time, the standard market risk premium is significant. Recall that the results of regression model (9.3) are not interpretable due to the high multicollinearity exhibited for the three estimated betas. This is also the case when we use the alternative proxy (*IQ'*). Table 3 reports that while none of the four estimated beta-coefficients are

[19] DD show that firms with larger standard deviations have less persistent earnings, longer operating cycles, larger accruals, and more volatile cash flows, accruals and earnings, suggesting lower accruals quality.

[20] When we estimate equation (10) in year *t*, we have to include *CFO* at three years, *t*-1, *t*, and *t*+1. In addition, *CFO* is defined as the difference between net income and total accruals. In other words, *CFO* at time *t*-1 has to include accounting components at time *t*-2. Therefore, estimating equation (10) in year *t* requires accounting information from year t-2 through *t*+1 and estimating this equation at year *t*-4 requires accounting information back to year *t*-6. In short, estimating the standard deviation proxy with the DD model requires a total of eight years of accounting information including six prior years.

statistically insignificant the R^2 of this specification is the highest of all reported regression specifications (0.309). Overall, the evidence of tests using the alternative information-quality proxy provides strong support for the general idea in our model, that the information-quality effect is manifested in priced systematic risk.

5.3 An IQ Proxy based on Statement of Cash Flows Information

In the above estimation of *IQ* (the absolute value of the estimated residual of the DD model), we use information from the balance sheet and income statement rather than from statement of cash flows. However, Hribar and Collins (2002) suggest that studies that use balance sheet accruals estimates are potentially biased. The bias is larger around major financing events such as mergers and acquisitions, because these events affect the numbers in consecutive balance sheets. Therefore, we also estimate equation (10) based on information from the statement of cash flows and we use cash flows from operations reported under the Statement of Financial Accounting Standards No.95 (SFAS No.95, FASB 1987). Following Hribar and Collins (2002), we define

$TCA = EBXI - OCF$,

where

EBXI = earnings before extraordinary items and discontinued operations, and

OCF = operating cash flow (from continuing operations) taken directly from the cash-flow statement.

To compute the cash-flow based *IQ* proxy we require statement of cash flow data that are not available prior to 1988. Recall that the estimation based on equation (10) requires four consecutive years of data (the estimation year, two years prior to the estimation year, and one year after the estimation year). Given that our test portfolios are formed based on the previous-year *IQ* proxy, with the cash-flow based proxy we obtain monthly test-portfolio *IQ* measures and returns for the January 1991 to December 2010 (20-year) period. This is much shorter relative to the 38-year sample of monthly test-portfolio data based on the *IQ* proxy used in the previous section, which is measured with information from the balance sheet and income statement. Thus, the increased accuracy resulting from using cash-flow statement data comes at a great cost of a significantly shorter sample period.

In Table 4 we report results based on the *IQ* proxy derived from the statement of cash flows. The results reported in this table are in line with the results reported in the previous section for test portfolios based on data for the balance sheet and income statement. Once again, the results provide strong support for the unconditional version of model. Hence, the support for our model is robust with respect to whether we sue equal- or value-weighted market portfolio in our tests. One apparent difference, is the substantially higher R^2 observed for all model specifications with the cash-flow based *IQ* proxy portfolios compared with that obtained for portfolios formed based on *IQ computed* from balance sheet and income statement data. We attribute this result to the shorter (20-year) sample period used here, which is likely to be less noisy relative to the 38-year sample of monthly test-portfolio data based on the *IQ* proxy used in the previous section.

Table 4 Here

5.4 Information-Quality Risk vs. Liquidity Risk

Disparity of information quality and/or quantity across different investors (i.e., asymmetric information), can adversely affect market liquidity (see Kyle, 1985; Glosten and Milgrom, 1985; and Easley and O'Hara, 1987). Thus, one may expect poor information-quality firms to also suffer from weak market liquidity. Given the strong support provided by Acharya and Pedersen (2005) for the pricing of systematic liquidity risk, the probable association between information quality and liquidity calls for further tests. Therefore, our next robustness test examines whether the significant pricing of our systematic information-quality risk still stands in the presence of Acharya and Pedersen's (2005) systematic liquidity risk.

Acharya and Pedersen (2005) use the normalized illiquidity measure of Amihud (2002) to estimate systematic-liquidity risk based on their theory.[21] To test whether our empirical support for the pricing of systematic information-quality risk is robust with

[21] Earlier studies examine the systematic nature of liquidity. Chordia, Subrahmanyam, and Anshuman (2000) show that stock returns are cross sectionally related to the variability in liquidity, where liquidity is proxied by measures such as trading volume and turnover. Chordia, Roll, and Subrahmanyam (2000), Huberman and Halka (1999), and Hasbrouck and Seppi (2000) find that individual stock liquidity co-moves with market-wide liquidity. Pastor and Stambaugh (2003) show that market-wide liquidity is a priced factor for stock returns.

respect to the inclusion of systematic liquidity risk, we estimate the following three-beta regression model:

$$E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ}\beta_p^{IQ} + \pi^{ILLIQ}\beta_p^{ILLIQ}, \qquad p=1,2,..25, \qquad (11)$$

where β_p^{ILLIQ} is Acharya and Pedersen's (2005) net illiquidity beta. This regression model considers three distinct sources of systematic risk: the standard CAPM market risk (β_p^{Market}), our systematic (aggregate) information-quality risk (β_p^{IQ}), and Acharya and Pedersen's (2005) systematic liquidity risk (β_p^{ILLIQ}).

The net illiquidity beta, β_p^{ILLIQ}, is a linear combination of Acharya and Pedersen's (2005) three liquidity betas. The illiquidity cost used in Acharya and Pedersen (2005) is constructed based on the absolute return-to-volume measure of Amihud (2002), which captures the price-impact dimension of liquidity, and has often been used in the empirical microstructure literature. [22] Following Amihud (2002), a market-illiquidity illiquidity measure for stock *i* in month *t* is given by:

$$ILLIQ_t^i = \frac{1}{Days_t^i}\sum_{d=1}^{Days_t^i}\frac{|R_{td}^i|}{V_{td}^i},$$

where R_{td}^i and V_{td}^i are the return and dollar volume (in millions) on day *d* in month *t*, respectively, and $Days_t^i$ is the number of observation days in month *t* for stock *i*.

To estimate $ILLIQ_t^i$ and β_p^{ILLIQ}, we sample all eligible stocks over a period corresponding to the period for which we form our *IQ*-based test portfolio (so that we obtain *ILLIQ* measures for the January 1977 to December 2010 period). Daily return and volume data are obtained from CRSP. Similar to the procedure for forming *IQ* portfolios outlined in the previous section, we form an equally-weighted market portfolio for each month *t* during the sample period, in which market return, market *IQ*, and market *ILLIQ* are computed.

[22] Hasbrouck (2002) uses microstructure data for NYSE, AMEX, and NASDAQ stocks to compute a measure of Kyle's lambda. He finds that it is highly correlated with Amihud's (2002) illiquidity measure and concludes that Amihud's measure is the most adequate among several considered market-liquidity proxies.

We form 25 test portfolios sorted on *IQ*. We form both value- and equal-weighted test portfolios. For each portfolio, we estimate β_p^{Market} and β_p^{IQ} following the procedures described in the previous section. We estimate β_p^{ILLIQ} following Acharya and Pedersen's (2005). We use an AR(2) specification to test for the autocorrelation pattern of market portfolio *ILLIQ* measure, and the resulting innovations in market portfolio *ILLIQ* appear stationary.

Table 5 documents the GMM coefficient estimates for regression model (11) for both value- and equal-weighted test portfolios. The regression coefficient of our systematic information-quality risk (β_p^{IQ}) is statistically significant at the 1% level for both equal-weighted and value-weighted portfolios. At the same time, we find that the Acharya and Pedersen's (2005) systematic liquidity risk (β_p^{ILLIQ}) is statistically insignificant. These results demonstrate that evidence in support of the pricing of our systematic information-quality risk is robust with respect to the inclusion of systematic liquidity risk.

Table 5 Here

6. Summary and Conclusions

We derive an intertemporal asset-pricing model in the spirit of Merton (1973) that allows us to investigate different channels through which systematic risk associated with imprecise accounting information affects asset prices. We show that in our model imprecise-information risk has systematic and idiosyncratic components, and only the former is priced. A static version of our model demonstrates that systematic information-quality risk is priced through the alteration of the market risk premium as well as through three extra asset betas. In our model, a market-wide required excess return due to imprecise information is distinct from the CAPM market risk premium. This addresses criticism of the lack of theoretical underpinning for the inclusion of a separate information-quality factor in empirical multiple-factor models such as that of Francis et al. (2005).

The three extra betas in our model represent three distinct systematic risk effects of imprecise accounting information for which investors demand an extra risk premium.

Our first information-imprecision beta reflects the security-return sensitivity with respect to market-wide information imprecision. This beta provides further theoretical support for the cross-sectional pricing of the Francis et al. (2005) information-quality factor loading. In the multiple-regression model in their paper, the security return is regressed on the market-wide information-quality factor, which means that, like our first information-imprecision beta, their information-quality factor loading is a function of the covariance between the security return and the market information-quality factor.

The remaining two information-precision betas are unique to our paper. The commonality in information quality beta is the second channel through which imprecise-information risk affects asset prices in our model. This beta reflects the co-movement between the information-imprecision return error of the individual asset and that of the market. To hedge against adverse imprecise-information effects on their portfolio, investors prefer to include an asset with a negative commonality beta, so that when information-imprecision depresses market returns it inflates the asset return.

The third and last channel, through which risk associated with imprecise information affects asset pricing in our model, is the beta that reflects the relation between the asset return errors due to imprecise-information and the precise market return. To protect their portfolio at times of a bearish market, investors prefer a security for which this relation is negative, so that when their portfolio is down the security tends to pay a positive imprecise-information return error. This unique result implies that investors may have a preference for investing in stocks issued by firms that erroneously or intentionally, release false positive information about the firm at times of a down market. This implication of our model raises the question of whether, empirically, at times of a depressed market investors prefer to invest in firms performing earnings management or management manipulation of management earnings forecast that improve expectations about the firm's future performance. This empirical question is left for future research.

We document strong empirical support for the pricing of our systematic information-quality risk. This evidence is robust to the information-imprecision return error proxy we use as well as to the test-portfolio and market-portfolio formation methodology. We further document that our systematic information-quality risk does not proxy for the well-documented systematic liquidity risk.

Appendix A – Derivation of the Wealth-Accumulation Process

Recall that the wealth accumulation equation for the l^{th} investor is given by:

$$dW = \sum_{i=1}^{n} q_i W d\tilde{r}_i + (1 - \sum_{i=1}^{n} q_i) W r_f - cdt \,, \tag{3}$$

Substituting for $d\tilde{r}$ from equation (2) we rewrite equation (3) as:

$$dW = \left[\sum_{i=1}^{n} q_i (\mu_{r_i} + k(\mu_{\psi_i} - \psi_i) - r_f) + r_f \right] Wdt + \sum_{i=1}^{n} q_i W \sqrt{\sigma_{r_i}^2 + \sigma_{\psi_i}^2 + 2\sigma_{r_i,\psi_i}} \, d\varpi_i - cdt. \tag{3.1}$$

where r_f is an exogenous instantaneous interest rate on a risk-free bond, and $\sum_{i=1}^{n+1} q_i = 1$, where q_{n+1} is the weight of the riskless asset. The assumption of constant risk-free rate in our model allows us to simplify our analysis and focus on the stock market.

The necessary instantaneous optimality condition for solving for an investor's consumption-investment optimal choice is as follows:

$$0 = \max_{c,q} [U(c,t)dt + J_t dt + J_W \mathrm{E}_t(dW) + \frac{1}{2} J_{WW} E(dW)^2 + \sum_{i=1}^{n} J_{\psi_i} \mathrm{E}_t(d(\psi_i)) \tag{3.2}$$

$$+ \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} J_{\psi_i \psi_j} E(d\psi_i d\psi_j) + \sum_{i=1}^{n} J_{W\psi_i} E(dWd\psi_i) + o(dt)].$$

Equation (3.2) implies a Gaussian process of wealth accumulation. Thus the variance and covariance of the instantaneous change in wealth and the instantaneous change in the observable noisy return are given by:

$$E_t(dW) = [\sum_1^n q_i (\mu_{r_i} + \mu_{\psi_i} - r_f) + r_f - c] dt, \tag{3.3}$$

$$E(dW)^2 = \sum_1^n \sum_1^n q_i q_j W^2 (\sigma_{r_i,r_j} + \sigma_{\psi_i,\psi_j} + \sigma_{r_i,\psi_j} + \sigma_{r_j,\psi_i}) dt, \tag{3.4}$$

$$E(d\psi_i d\psi_j) = \sigma_{\psi_i} \sigma_{\psi_j} \rho_{\psi_i,\psi_j} dt, \tag{3.5}$$

$$E(dWd\psi_j) = \sum_{i=1}^{n} q_i W (\sigma_{r_i,\psi_j} + \sigma_{\psi_i,\psi_j}) dt. \tag{3.6}$$

Substituting equations (3.3) to (3.6) into equation (3.2), we get the following equation,

$$
\begin{aligned}
0 = \max[&U(c,t) + J_t + J_W[(\sum_1^n q_i(\mu_{r_i} + \mu_{\psi_i} - r_f) + r_f)W] \\
&+ \frac{1}{2} J_{WW} \sum_1^n \sum_1^n q_i q_j (\sigma_{r_i,r_j} + \sigma_{\psi_i,\psi_j} + \sigma_{r_i,\psi_j} + \sigma_{r_j,\psi_i}) W^2 \\
&+ \frac{1}{2} \sum_1^n \sum_1^n J_{\psi_i \psi_j} \sigma_{\psi_i} \sigma_{\psi_j} \rho_{\psi_i,\psi_j} \\
&+ \sum_1^n \sum_1^n J_{W\psi_j} q_i W (\sigma_{r_i,\psi_j} + \sigma_{\psi_i,\psi_j}).
\end{aligned} \tag{4}
$$

The n+1 first-order conditions for each investor derived from equation (4) are given by:

$$0 = U_c(c,t) - J_W(W,t,\psi), \tag{4.1}$$

$$
\begin{aligned}
0 = &J_W(\mu_{r_i} + \mu_{\psi_i} - r_f)W + J_{WW} \sum_{j=1}^n q_j W^2 (\sigma_{r_i,r_j} + \sigma_{\psi_i,\psi_j} + \sigma_{r_i,\psi_j} + \sigma_{r_j,\psi_i}) \\
&+ \sum_{j=1}^n J_{W\psi_j} W (\sigma_{r_i,\psi_j} + \sigma_{\psi_i,\psi_j}),
\end{aligned} \tag{4.2}
$$

$\forall \ i = 1,2,...n,$ where $c^* = c(W,t,\psi)$ and $q_i^* = q_i(W,t,\psi)$ are optimal solutions for equations (4.1) and (4.2) as functions of the perceived state variables.

Using matrix notation, we rewrite equation (4.2) for the n risky assets as follows:

$$0 = J_W(\mu_r + \mu_\psi - r_f I) + J_{WW} W \Sigma_{\tilde{r},\tilde{r}} q + \Sigma_{\tilde{r},\psi} J_{W\psi}, \tag{5}$$

where μ_r is the vector of mean precise returns of the n risky securities, μ_ψ is the vector of long-term means of information-imprecision return error (which are also the long-term return spreads between the precise returns and imprecise returns), ψ is the row-vector of firm-specific information-related return error, $\Sigma_{\tilde{r},\tilde{r}}$ is the variance-covariance matrix of imprecise returns with elements $\sigma_{\tilde{r}_i,\tilde{r}_j} = \sigma_{r_i,r_j} + \sigma_{\psi_i,\psi_j} + \sigma_{r_i,\psi_j} + \sigma_{r_j,\psi_i}$, and $\Sigma_{\tilde{r},\psi}$ is the matrix of covariance terms between observed noisy return variables and the information-related return errors on risky asset, with components given by $\sigma_{\tilde{r}_i,\psi_j} = (\sigma_{r_i,\psi_j} + \sigma_{\psi_i,\psi_j}),$

$\forall \ i = 1,2,...n, \ and \ \ j = 1,2,...n.$

Solving equation (5), we obtain the vector of optimal portfolio weights for the n risky securities:

$$q^* = -\frac{J_W}{WJ_{WW}} \Sigma_{\tilde{r},\tilde{r}}^{-1} (\mu_r + \mu_\psi - r_f I) - \Sigma_{\tilde{r},\tilde{r}}^{-1} \Sigma_{\tilde{r},\psi} \frac{J_{W\psi}}{WJ_{WW}}. \tag{5.1}$$

Equation (5.1) can be written for every asset *i* as follows:

$$q_i^* = -\frac{J_W}{WJ_{WW}} \sum_{j=1}^{n} v_{\tilde{r}_i,\tilde{r}_j} (\mu_{r_j} + \mu_{\psi_j} - r_f I_j) - \sum_{j,k=1}^{n} v_{\tilde{r}_i,\tilde{r}_j} (\sigma_{r_j,\psi_k} + \sigma_{\psi_j,\psi_k}) \frac{J_{W\psi_k}}{WJ_{WW}}, \tag{5.2}$$

$\forall\ i = 1,2,...n,\ \ j = 1,2,...n,$ and $k = 1,2,...n.$ $v_{\tilde{r}_i,\tilde{r}_j}$ denotes an element in the inverse of the variance covariance matrix, that is $\Sigma^{-1}_{\tilde{r}_i,\tilde{r}_j}$. Equation (5.2) gives the optimal weights (demand) for risky assets in the presence of imprecise accounting information.

Appendix B – Derivation of Equilibrium Pricing Equation (6)

Equation (5) can be rearranged as follows:

$$a^l(\mu_r + \mu_\psi - r_f 1) = -W^l \Sigma_{\tilde{r},\tilde{r}} q^l - \Sigma_{\tilde{r},\psi} b^l, \tag{5.3}$$

where $a^l = (\frac{J_W}{J_{WW}})^l$ and vector $b^l = (\frac{J_{W\psi}}{J_{WW}})^l$, for investor *l*, *l* = 1, 2,…, *L*. Summing across the *L* investors and dividing by $\sum_1^L a^l$, we obtain:

$$\mu_r + \mu_\psi - r_f 1 = -A\Sigma_{\tilde{r},\tilde{r}} \frac{\sum_1^L W^l q^l}{\sum_1^L W^l} - \Sigma_{\tilde{r},\psi} B = -A\Sigma_{\tilde{r},\tilde{r}} x_m - \Sigma_{\tilde{r},\psi} B, \tag{5.4}$$

where $A = \frac{\sum_1^L W^l}{\sum_1^L a^l}$ is a scalar, $B = \frac{\sum_1^L b^l}{\sum_1^L a^l}$ is an $n \times 1$ vector, and $x_m = \frac{\sum_1^L W^l q^l}{\sum_1^L W^l}$ is a vector of market equilibrium security weights. This notation allows us to write: $\Sigma_{\tilde{r},\tilde{r}} x_m = \underbrace{\sigma_{\tilde{r},\tilde{r}_m}}_{n\times 1} = \underbrace{(\sigma_{r,r_m} + \sigma_{\psi,r_m} + \sigma_{r,\psi_m} + \sigma_{\psi,\psi_m})}_{n\times 1},$ $x_m^T \Sigma_{\tilde{r},\psi} = \underbrace{\sigma_{\tilde{r}_m,\psi}}_{1\times n} = \underbrace{(\sigma_{r_m,\psi} + \sigma_{\psi_m,\psi})}_{1\times n},$ and $x_m^T \Sigma x_m = \sigma^2_{\tilde{r}_m}$.

To compute *A* and *B* in terms of first and second moments of the tangency and hedge portfolios as well as covariance terms of individual returns with these portfolios, we pre-multiply equation (5.4) by weight vectors, x_m^T, and $y_{h,k}^T$, $k = 1,2,...n,$ respectively, to yield the following *n*+1 equations:

$$\mu_{r_m} + \mu_{\psi_m} - r_f = -A\sigma^2_{\tilde{r}_m} - \sigma_{\tilde{r}_m,\psi} B, \tag{5.5}$$

$$\mu_{r_{h,k}} + \mu_{\psi_{h,k}} - r_f = -A\sigma_{\tilde{r}_{h,k},\tilde{r}_m} - \sigma_{\tilde{r}_{h,k},\psi}B, \quad k = 1,2,...n, \tag{5.6}$$

where $\mu_{r_m} = \sum_{i=1}^{n} x_i \mu_{r_i}$ is the weighted expected precise return for the market portfolio, $\mu_{\psi_m} = \sum_{i=1}^{n} x_i \mu_{\psi_i}$ is the weighted mean of the information-imprecision return error for the market portfolio, $\psi_m = \sum_{i=1}^{n} x_i \psi_i$ is the market-wide weighted imprecise-information-related return error, and x_m is an $n\times 1$ vector of security weights in the market portfolio with elements x_i. Similarly, for the hedge portfolios, $\mu_{r_{h,k}} = \sum_{i=1}^{n} y_{i,k}\mu_{r_i}$ is the weighted expected precise return on hedge portfolio *k*, the term $\mu_{\psi_{h,k}} = \sum_{i=1}^{n} y_{i,k}\mu_{\psi_i}$ is the weighted mean of imprecise-information return error on hedge portfolio *k*, $\psi_{h,k} = \sum_{i=1}^{n} y_{i,k}\psi_i$ represents the weighted imprecise-information return error inherent in hedge portfolio *k*, and $y_{h,k}$ is an $n\times 1$ vector of security weights in hedge portfolio *k* with elements $y_{i,k}$.

Solving for *A* from equation (5.5), we have:

$$-A = \frac{\mu_{r_m} + \mu_{\psi_m} - r_f + \sigma_{\tilde{r}_m,\psi}B}{\sigma^2_{\tilde{r}_m}}. \tag{5.7}$$

Next, let μ_{r_h} denote an $n\times 1$ vector with elements $\mu_{r_{h,k}}$, μ_{ψ_h} is an $n\times 1$ vector with elements $\mu_{\psi_{h,k}}$, and ψ_h denotes an $n\times 1$ vector with elements $\psi_{h,k}$. Substituting the above solution to *A* into equation (5.5) and simplifying leads to:

$$\mu_{r_h} + \mu_{\psi_h} - r_f 1 = \frac{\sigma_{\tilde{r}_h,\tilde{r}_m}}{\sigma^2_{\tilde{r}_m}}(\mu_{r_m} + \mu_{\psi_m} - r_f) + \left(\frac{\sigma_{\tilde{r}_h,\tilde{r}_m}}{\sigma^2_{\tilde{r}_m}}\sigma_{\tilde{r}_m,\psi} - \sigma_{\tilde{r}_h,\psi}\right)B.$$

Define $\Gamma_{\tilde{r}}$ and $\Gamma_{\tilde{r}_h}$ as

$$\underbrace{\Gamma_{\tilde{r}}}_{n\times n} = \beta^m \Sigma_{\tilde{r}_m,\psi} - \Sigma_{\tilde{r},\psi}, \text{ where } \underbrace{\beta^m}_{n\times 1} = \frac{\sigma_{\tilde{r},\tilde{r}_m}}{\sigma^2_{\tilde{r}_m}}.$$

$$\underbrace{\Gamma_{\tilde{r}_h}}_{n\times n} = \beta^h \Sigma_{\tilde{r}_m,\psi} - \Sigma_{\tilde{r}_h,\psi}, \text{ where } \underbrace{\beta^h}_{n\times 1} = \frac{\sigma_{\tilde{r}_h,\tilde{r}_m}}{\sigma^2_{\tilde{r}_m}}.$$

Assuming that the inverse matrix $\Gamma^{-1}_{\tilde{r}_h}$ exists, we solve for B

$$B = \Gamma_{\tilde{r}_h}^{-1}[\mu_{r_h} + \mu_{\psi_h} - r_f 1 - \beta^h(\mu_{r_m} + \mu_{\psi_m} - r_f)]$$
$$= \Gamma_{\tilde{r}_h}^{-1}\pi^h - \beta^h \pi^m, \qquad (5.8)$$

where $\pi^m = (\mu_{r_m} - r_f) + \mu_{\psi_m}$ represents the imprecise-information-adjusted market risk premium, and $\pi^h = (\mu_{r_h} - r_f) + \mu_{\psi_h}$ is a $n \times 1$vector of hedge portfolio risk premiums.

Substituting solutions (5.7) and (5.8) for A and B into equation (5.4), we obtain the following result:

$$\mu_r + \mu_\psi - r_f 1 = -A\sigma_{\tilde{r},\tilde{r}_m} - \sigma_{\tilde{r},\psi} B$$
$$= \frac{\sigma_{\tilde{r},\tilde{r}_m}}{\sigma^2_{\tilde{r}_m}}\pi^m + \left(\frac{\sigma_{\tilde{r},\tilde{r}_m}}{\sigma^2_{\tilde{r}_m}}\sigma_{\tilde{r}_m,\psi} - \sigma_{\tilde{r},\psi}\right)B$$
$$= \beta^m \pi^m + \Gamma_{\tilde{r}}\Gamma_{\tilde{r}_h}^{-1}[\pi^h - \beta^h \pi^m], \qquad (5.9)$$

where the term $[\pi^h - \beta^h \pi^m]$ is the vector of mean pricing errors of the hedge portfolios, determined by hedge portfolio return sensitivities to the market portfolio.

Substituting for $\Gamma_{\tilde{r}}$ and $\Gamma_{\tilde{r}_h}$, we rewrite Equation (5.9) to obtain our imprecise-information-adjusted asset-pricing equation:

$$\mu_{r_i} + \mu_{\psi_i} - r_f = \beta_i^m(\mu_{r_m} - r_f) + \beta_i^m \mu_{\psi_m} + H_i, \qquad (6)$$

where $\beta_i^m = \dfrac{\sigma_{\tilde{r}_i,\tilde{r}_m}}{\sigma^2_{\tilde{r}_m}}$, and $H_i = \sum_{k=1}^n \sum_{j=1}^n (\beta_i^m \sigma_{\tilde{r}_m,\psi_j} - \sigma_{\tilde{r}_i,\psi_j}) b_{\tilde{r}_{h,j},\tilde{r}_{h,k}} (\pi_k^h - \beta_k^h \pi^m)$

$(\beta_i^m \sigma_{\tilde{r}_m,\psi_j} - \sigma_{\tilde{r}_i,\psi_j})$ is an element of the $n \times n$ matrix $\Gamma_{\tilde{r}}$, $\forall\ i = 1,2,...n$, and $j = 1,2,...n$; $b_{\tilde{r}_{h,j},\tilde{r}_{h,k}}$ represents an element of the inverse matrix $\Gamma_{\tilde{r}_h}^{-1}$, $\forall\ j = 1,2,...n$, and $k = 1,2,...n$; and $(\pi_k^h - \beta_k^h \pi^m)$ reflects the k^{th} hedge portfolio's mean pricing error under CAPM, $\forall$ $k = 1,2,...n$.

Table A.1 Here

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Table 1: *IQ*-Sorted Portfolios with an Equal-Weighted Market

This table reports the coefficient estimates from cross-sectional regressions of our static model for 25 value-weighted (Panel A) and equal-weighted (Panel B) portfolios, using monthly data during January 1970 to December 2010, with an equal-weighted market portfolio. We use GMM to obtain the coefficient estimates and *t*-statistics (in parentheses) based on the following model specifications:

CAPM $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl}$,

(9.1) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi\beta_p^{All}$,

(9.2) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ}\beta_p^{IQ}$,

(9.3) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ,1}\beta_p^{IQ} + \pi^{IQ,2}\beta_p^{IQ,2} + \pi^{IQ,3}\beta_p^{IQ,3}$,

where $\beta_p^{All} = \beta_p^{Market} + \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$ and $\beta_p^{IQ} = \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$. The table also reports the R^2 and the adjusted-R^2 (in parentheses). *** represents significance at 1%; ** significance at 5%; and * significance at 10%.

	alpha	β_p^{Market}	$\beta_p^{IQ,1}$	$\beta_p^{IQ,2}$	$\beta_p^{IQ,3}$	β_p^{All}	β_p^{IQ}	R^2
Panel A: Value-weighted portfolios								
CAPM	0.002	0.012***						0.455
	(1.480)	(5.910)						(0.431)
	0.007		1.316***					0.180
	(5.470)		(3.010)					(0.145)
	0.011			1.803***				0.348
	(56.970)			(6.240)				(0.320)
	0.011				0.040***			0.554
	(39.130)				(6.680)			(0.535)
9.1	0.003					0.011***		0.554
	(2.450)					(6.350)		(0.435)
9.2	0.007	0.006**					0.028***	0.621
	(3.910)	(2.480)					(5.990)	(0.586)
9.3	0.007	0.002	0.934**	-1.668*	0.059***			0.709
	(3.490)	(0.710)	(2.680)	(-2.05)	(3.640)			(0.651)
Panel B: Equal-weighted portfolios								
CAPM	0.003	0.007**						0.201
	(1.380)	(2.800)						(0.167)
	0.010		0.001					0.001
	(6.150)		(0.001)					(-0.044)
	0.010			1.177***				0.560
	(81.870)			(7.550)				(0.436)
	0.010				0.022***			0.512
	(67.820)				(7.350)			(0.491)
9.1	0.004					0.006***		0.332
	(1.950)					(3.110)		(0.303)
9.2	0.011	-0.002					0.025***	0.515
	(5.390)	(-0.86)					(6.920)	(0.471)
9.3	0.012	0.003	-0.927*	-1.658	0.052*			0.618
	(4.220)	(0.620)	(-1.88)	(-1.14)	(1.780)			(0.542)

Table 2: *IQ*-Sorted Portfolios with a Value-Weighted Market

This table reports the coefficient estimates from cross-sectional regressions of our static model for 25 value-weighted (Panel A) and equal-weighted (Panel B) portfolios, using monthly data during January 1970 to December 2010, with a value-weighted market portfolio. We use GMM to obtain the coefficient estimates and *t*-statistics (in parentheses) based on the following model specifications:

CAPM $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market} \beta_p^{Marketl}$,

(9.1) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi \beta_p^{All}$,

(9.2) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market} \beta_p^{Marketl} + \pi^{IQ} \beta_p^{IQ}$,

(9.3) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market} \beta_p^{Marketl} + \pi^{IQ,1} \beta_p^{IQ} + \pi^{IQ,2} \beta_p^{IQ,2} + \pi^{IQ,3} \beta_p^{IQ,3}$,

where $\beta_p^{All} = \beta_p^{Market} + \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$ and $\beta_p^{IQ} = \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$. The table also reports the R^2 and the adjusted-R^2 (in parentheses). *** represents significance at 1%; ** significance at 5%; and * significance at 10%.

	alpha	β_p^{Market}	$\beta_p^{IQ,1}$	$\beta_p^{IQ,2}$	$\beta_p^{IQ,3}$	β_p^{All}	β_p^{IQ}	R^2
Panel A: Value-weighted portfolios								
CAPM	0.002	0.010***						0.281
	(1.110)	(5.360)						(0.250)
	0.006		0.803***					0.479
	(5.570)		(5.510)					(0.456)
	0.011			1.014***				0.380
	(49.560)			(5.480)				(0.353)
	0.011				0.047***			0.467
	(37.440)				(5.730)			(0.444)
9.1	0.001					0.011***		0.414
	(0.640)					(5.590)		(0.389)
9.2	0.005	0.006**					0.038***	0.576
	(2.590)	(2.660)					(7.320)	(0.538)
9.3	0.006	0.002	0.420	0.021	0.030*			0.612
	(3.270)	(0.620)	(1.410)	(0.050)	(2.080)			(0.535)
Panel B: Equal-weighted portfolios								
CAPM	0.005	0.005**						0.059
	(1.800)	(2.200)						(0.018)
	0.008		0.227					0.056
	(6.360)		(1.480)					(0.015)
	0.010			1.040***				0.467
	(81.780)			(7.640)				(0.444)
	0.010				0.037***			0.538
	(71.840)				(7.860)			(0.518)
9.1	0.002					0.008**		0.209
	(0.580)					(2.670)		(0.175)
9.2	0.012	-0.002					0.036***	0.531
	(4.470)	(-0.72)					(7.600)	(0.488)
9.3	0.007	0.006	-0.428*	-0.725	0.069***			0.600
	(2.260)	(1.400)	(-1.92)	(-1.30)	(3.610)			(0.520)

Table 3: Using an Alternative *IQ* Proxy

This table reports the coefficient estimates from cross-sectional regressions of our static model for 25 value-weighted portfolios sorted on *IQ'*, using monthly data during January 1970 to December 2010, with an equal-weighted market portfolio. The alternative proxy is given by the standard deviation of firm *i*'s cross-sectional regression residuals across five years: $IQ' = \sigma(e_{it}, e_{it-1}, e_{it-2}, e_{it-3}, e_{it-4})$. We estimated this proxy using balance sheet data. We use GMM to obtain the coefficient estimates and *t*-statistics (in parentheses) based on the following model specifications:

CAPM $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl}$,

(9.1) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi\beta_p^{All}$,

(9.2) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ}\beta_p^{IQ}$,

(9.3) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ,1}\beta_p^{IQ} + \pi^{IQ,2}\beta_p^{IQ,2} + \pi^{IQ,3}\beta_p^{IQ,3}$,

where $\beta_p^{All} = \beta_p^{Market} + \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$ and $\beta_p^{IQ} = \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$. The table also reports the R^2 and the adjusted-R^2 (in parentheses). *** represents significance at 1%; ** significance at 5%; and * significance at 10%.

	alpha	β_p^{Market}	$\beta_p^{IQ,1}$	$\beta_p^{IQ,2}$	$\beta_p^{IQ,3}$	β_p^{All}	β_p^{IQ}	R^2
CAPM	0.004	0.010***						0.144
	(1.690)	(2.990)						(0.107)
	0.012		-0.075					0.001
	(13.600)		(-0.11)					(-0.043)
	0.011			1.037***				0.253
	(50.750)			(4.180)				(0.221)
	0.011				0.029***			0.235
	(50.100)				(3.300)			(0.201)
9.1	0.004					0.009***		0.224
	(1.960)					(3.270)		(0.190)
9.2	0.008	0.004					0.024**	0.278
	(2.780)	(1.140)					(2.260)	(0.212)
9.3	0.007	0.005	0.135	0.573	0.012			0.309
	(2.560)	(1.290)	(0.200)	(0.940)	(0.650)			(0.171)

Table 4: Using Cash-flow Statement Data

This table reports the coefficient estimates from cross-sectional regressions of our static model for 25 value-weighted portfolios sorted on *IQ*, using monthly data during January 1988 to December 2010, with an equal-weighted market portfolio. The *IQ* proxy is estimated using information from the statement of cash flows (instead of information from the balance sheet and income statement). We use GMM to obtain the coefficient estimates and *t*-statistics (in parentheses) based on the following model specifications:

CAPM $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl}$,

(9.1) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi\beta_p^{All}$,

(9.2) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ}\beta_p^{IQ}$,

(9.3) $E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ,1}\beta_p^{IQ} + \pi^{IQ,2}\beta_p^{IQ,2} + \pi^{IQ,3}\beta_p^{IQ,3}$,

where $\beta_p^{All} = \beta_p^{Market} + \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$ and $\beta_p^{IQ} = \beta_p^{IQ,1} + \beta_p^{IQ,2} + \beta_p^{IQ,3}$. The table also reports the R^2 and the adjusted-R^2 (in parentheses). *** represents significance at 1%; ** significance at 5%; and * significance at 10%.

	alpha	β_p^{Market}	$\beta_p^{IQ,1}$	$\beta_p^{IQ,2}$	$\beta_p^{IQ,3}$	β_p^{All}	β_p^{IQ}	R^2
CAPM	(0.001)	0.018***						0.781
	(-0.36)	(8.600)						(0.771)
	0.012		-0.986***					0.306
	(19.110)		(-3.83)					(0.276)
	0.013			3.021***				0.567
	(34.790)			(5.340)				(0.548)
	0.010				0.079***			0.567
	(16.520)				(7.260)			(0.548)
9.1	0.001					0.016***		0.803
	(1.070)					(12.540)		(0.795)
9.2	0.002	0.014***					0.025***	0.807
	(1.280)	(6.080)					(3.190)	(0.789)
9.3	0.003	0.013***	-0.062	0.164	0.025*			0.808
	(1.210)	(3.280)	(-0.23)	(0.260)	(1.980)			(0.770)

Table 5: Information-Quality Risk vs. Liquidity Risk

This table reports the coefficient estimates from the cross-sectional regression model (11) for 25 value-weighted (Panel A) and equal-weighted (Panel B) portfolios, using monthly data during January 1970 to December 2010, with an equal-weighted market portfolio. We use GMM to obtain the coefficient estimates and *t*-statistics (in parentheses) based on the following model specifications:

(11) $$E(\tilde{r}_{pt} - r_{ft}) = \alpha + \pi^{Market}\beta_p^{Marketl} + \pi^{IQ}\beta_p^{IQ} + \pi^{ILLIQ}\beta_p^{ILLIQ},$$

where β_p^{Market} represents the standard CAPM market risk, β_p^{IQ} stands for our systematic (aggregate) information-quality risk, and β_p^{ILLIQ} represents Acharya and Pedersen's (2005) systematic liquidity risk. The table also reports the R^2 and the adjusted-R^2 (in parentheses). *** represents significance at 1%; ** significance at 5%; and * significance at 10%.

Alpha	β_p^{Market}	β_p^{IQ}	β_p^{ILLIQ}	R^2
Panel A: Value-weighted portfolios				
0.007	0.006**	0.029***	-0.017	0.622
(3.820)	(2.400)	(5.460)	(-0.39)	(0.569)
Panel B: Equal-weighted portfolios				
0.012	-0.003	0.020***	0.017	0.530
(5.280)	(-0.98)	(3.280)	(0.800)	(0.463)

Table A.1: Beta Correlations for the Test Portfolios

This table reports the Pearson correlations between the standard CAPM market beta and our three information-quality betas for the 25 value-weighted (Panel A) and equal-weighted (Panel B) portfolios. The table also reports *p*-values (in parentheses). *** represents significance at 1%; ** significance at 5%; and * significance at 10%.

Panel A: Value-weighted portfolios

	β_p^{Market}	$\beta_p^{IQ,1}$	$\beta_p^{IQ,2}$	$\beta_p^{IQ,3}$
β_p^{Market}	1.000	0.499**	0.556***	0.644***
		(0.011)	(0.004)	(0.001)
$\beta_p^{IQ,1}$		1.000	0.230	0.174
			(0.268)	(0.506)
$\beta_p^{IQ,2}$			1.000	0.902***
				(<.0001)
$\beta_p^{IQ,3}$				1.000

Panel B: Equal-weighted portfolios

	β_p^{Market}	$\beta_p^{IQ,1}$	$\beta_p^{IQ,2}$	$\beta_p^{IQ,3}$
β_p^{Market}	1.000	0.702***	0.661***	0.711***
		(<.0001)	(0.000)	(<.0001)
$\beta_p^{IQ,1}$		1.000	0.301	0.334
			(0.143)	(0.103)
$\beta_p^{IQ,2}$			1.000	0.984***
				(<.0001)
$\beta_p^{IQ,3}$				1.000