Cross-Sectional Dispersion of Firm Valuations and Expected Returns

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Cross-Sectional Dispersion of Firm Valuations and Expected Returns

Abstract

This paper develops two competing hypotheses for the relationship between cross-sectional standard deviation of firm fundamental-to-price ratios ("dispersion") and expected aggregate returns. In a model with fully rational beliefs, greater dispersion indicates greater risk and higher expected aggregate returns. In a model with heterogeneous beliefs generated by investor overconfidence, greater dispersion suggests more divergent beliefs and lower expected aggregate returns. Consistent with the model based on heterogeneous beliefs, (1) measures of dispersion are negatively related to subsequent market excess returns, and (2) this negative dispersion-return relationship is most pronounced among firm with high beta or high return volatility.

Introduction

It has been close to two decades since the discovery of the ability of the aggregate fundamental-to-price ratios (such as the dividend-to-price ratio and the book-to-market equity) to forecast stock market returns.[1] However, it has not been resolved whether this predictability stems from a simple discount rate effect or aggregate misvaluation.[2] The discount rate effect can occur in a perfectly rational market. However, misvaluation can only appear when an average investor is imperfectly rational and arbitrage is limited.

In addition to the debate at the aggregate level, there has been a similar ongoing debate about the positive relationship between firm-level fundamental-to-price ratios and the cross section of stock returns, known as the "value effect"(e.g., Fama & French (1992)). Again, the predictability at the firm-level can be due to either risk or misvaluation. A large and growing literature has arisen refining and testing the two explanations at the firm level.[3] Interestingly, there have been very few efforts to test the two competing explanations at the aggregate level.[4]

This paper takes a fresh approach to understand risk versus mispricing at the aggregate level. This new approach shifts from the usual focus on the cross-sectional mean of firm valuation ratios (i.e., the aggregate fundamental-to-price ratios) to the cross-sectional *standard deviation* of firm valuation ratios, which I call *dispersion*. I argue that the relationship between dispersion and aggregate stock returns helps to differentiate a behavioral story from a risk story.

Specifically, two simple stock market models are developed in this paper: one with fully rational beliefs and one with heterogeneous beliefs created by investor overconfidence.[5] The

[1]See Campbell & Shiller (1988), Fama & French (1988*a*) for the dividend yield; see Kothari & Shanken (1997), Pontiff & Schall (1998) for the book-to-market equity; see Lamont (1998) for the earnings-to-price ratio, and see Lee, Myers & Swaminathan (1999) for the value-to-price ratio. For recent evidence, see Lewellen (2004) and Ang & Bekaert (2006).

[2]With the discount rate effect, a positive shock to the expected return will result in a negative shock to the current price, which increases the current fundamental-to-price ratios (Fama & French (1988*a*)). Thus, a higher aggregate fundamental-to-price ratio should on average precede greater market returns. Based on the explanation of misvaluation, a high aggregate fundamental-to-price ratio is an indicator of stock market underpricing. When underpricing is subsequently corrected, future aggregate returns should be high (Lee et al. (1999)).

[3]Research in the rational paradigm links the return differentials between high and low fundamental-to-price ratio firms to their differences in risk (e.g., Fama & French (1995), Petkova & Zhang (2005)). Studies in the approach of behavioral finance provide evidence for valuation errors such as the concentration of price reversal upon earnings announcement (e.g., La Porta, Lakonishok, Shleifer & Vishny (1997), Skinner & Sloan (2002)).

[4]The earlier attempts were made by Kothari & Shanken (1997) and Pontiff & Schall (1998) to distinguish the two explanations.

[5]Overconfidence refers to the tendency to overestimate one's own signal precision. It has been frequently used to create disagreement in beliefs (e.g., Scheinkman & Xiong (2003)). In addition, overconfidence is

former generates the discount rate effect while the latter produces the misvaluation effect. Both models predict a positive relationship between aggregate fundamental-to-price ratios and expected aggregate returns. However, they deliver opposite predictions regarding the relationship between dispersion and expected aggregate returns. The model with perfect rationality predicts a positive relationship between the two while that based on heterogeneous beliefs suggests a negative relationship. Therefore, the dispersion-return relationship can help disentangle the two possible explanations.

To see the intuition, consider an equilibrium in which expected individual stock returns, which can be measured by the difference between measures of firm expected cash flows and stock price (denoted as $C - P$), are proportional to the expected market return according to firm beta. Put it in a simplified equation, $C_i - P_i = \beta_i E(R_m)$. Thus, cross-sectional standard deviation of firm $C - P$, $\sigma(C - P)$, is determined by $\sigma(\beta)\,|E(R_m)|$.

In a rational market, $E(R_m)$ is always positive. Thus, given the dispersion of beta, a positive shock to the market risk premium will lead to greater dispersion.[6] In contrast, in a market with both rational and overconfident investors, $|E(R_m)|$ reflects the divergent investor expectations about aggregate cash flows, which, when combined with limits of arbitrage, should precede lower aggregate returns.[7] Therefore, I can test the 'risk hypothesis' against the 'misvaluation hypothesis' by examining the relationship between firm valuation dispersion and subsequent aggregate returns.

In my empirical tests, I form a composite measure of cross-sectional dispersion of firm-level valuations that incorporates the cross-sectional standard deviations of three logarithmic firm valuation ratios: the book-to-market equity, the dividend-to-price ratio, and the earnings-to-price ratio, and call this composite measure *cross-firm valuation dispersion* (CVD).

My results support the misvaluation hypotheses. First, I find that CVD is positively correlated with the aggregate trading volume and aggregate idiosyncratic volatility and tends to rise after a period of good market performance. This evidence is consistent with prior theoretical and empirical research suggesting that more divergent beliefs or greater overconfidence generates larger trading volume, higher return volatility, and tends to grow after

widely identified by experimental studies in psychology and extensively developed by a growing finance literature to explain various stock market phenomena (e.g., Odean (1998), Daniel, Hirshleifer & Subrahmanyam (1998)).

[6]This prediction holds not only in an unconditional CAPM (as in my model) but also in a conditional CAPM of Gomes, Kogan & Zhang (2003).

[7]In this model, since investors underestimate risk due to overestimating signal precision, the expected aggregate returns are on average lower due to a lower risk premium required by investors. In the model section, I also discuss an alternative modeling approach that incorporates short-sale constraints instead of investor risk aversion. Similar to the model of Miller (1977), the combination of heterogeneous beliefs and short-sale constraints can lead to stock market overpricing and low expected market returns.

past trading success.[8] Thus, these results establish a link between CVD and heterogeneous beliefs on the stock market.

Second, I confirm the misvaluation hypothesis that CVD is a negative predictor of subsequent market excess returns at horizons as short as three months and as long as three years ahead. The predictive power of CVD persists after controlling for a set of well-known aggregate return predictors.[9] This empirical finding is related to the value-spread literature, in which the value spread is defined as the difference of the logarithmic book-to-market equity between the value firms and the growth firms (Cohen, Polk & Vuolteenaho (2003)).[10] My results extend this literature by demonstrating that (1) theoretically the value spread does not help disentangle risk from misvaluation while CVD does, and (2) empirically CVD is a stronger predictor of the aggregate returns than the value spread. Thus, this research also provides an alternative interpretation to the ability of the value spread to forecast equity premium.[11]

Third, consistent with the model prediction based on heterogeneous beliefs, I show that the negative dispersion-return relationship is more pronounced among riskier firms, such as firms with greater beta or larger return volatility. The top and the bottom beta (or volatility) quintiles differ sharply in their return sensitivity to the changes in CVD, and the differences in sensitivity are robust to controls for a set of well-known common factors.[12] This finding suggests that, while market beta measures the sensitivity of asset returns to aggregate risk, it also serves as an multiplier on aggregate mispricing, a prediction from the model with heterogeneous beliefs.

Finally, I document contrast cross-sectional return patterns across the states with high or low beginning-of-period CVD. For example, when the beginning-of-period CVD is relatively low–suggesting less divergent beliefs and smaller mispricing, the largest beta quintile *overperforms* its counterparts by 7.02% per annum. In contrast, when the beginning-of-period

[8] Theory: Odean (1998), Gervais & Odean (2001), and Scheinkman & Xiong (2003). Empirical research: Lee & Swaminathan (2000), Boehme, Danielsen & Sorescu (2006), and Statman, Thorley & Vorkink (2006).

[9] They include aggregate dividend yield (Campbell & Shiller (1988), Fama & French (1988*a*), Lewellen (2004)), short-term interest rate (Fama & Schwert (1977)), past market returns (Fama & French (1988*b*)), default premium and term premium (Fama & French (1989)), aggregate relative equity issuances (Baker & Wurgler (2000)), and the aggregate consumption-wealth ratio (*cay*) (Lettau & Ludvigson (2001)).

[10] This literature finds that the value spread forecasts one-month-ahead market excess returns (e.g., Brennan, Wang & Xia (2001), Campbell & Vuolteenaho (2004)).

[11] Brennan, Wang & Xia (2004) suggest that the value spread is a proxy for the state variable in an ICAPM. While inheriting the argument of Brennan et al., Campbell & Vuolteenaho (2004) also acknowledge other possible interpretations for the predictive power of the value spread, one of which is investor irrationality. However, this link between the value spread and investor irrationality has not been formally modeled in existing literature.

[12] The factors include the Fama-French 3 factors (Fama & French (1993)), the 4 factors that additionally includes a momentum factor (Carhart (1997)), and the ICAPM factors of Brennan et al. (2004).

dispersion is relatively high–indicating more divergent beliefs and greater mispricing, the largest beta quintile *underperforms* its counterparts by 7.09% per annum. The most noteworthy finding is that the top two riskiest quintiles on average earn *negative* excess returns during periods with high beginning-of-period dispersion. Consistent with my models, these findings suggest that, when investor irrational beliefs are relatively weak, risk dominates mispricing in shaping expected stock returns, and there is a positive risk-return trade-off. Conversely, when investor irrational beliefs are relatively strong, mispricing dominates risk in driving expected returns; thus the cross section of returns exhibit an anomalous negative risk-return relationship.

The remainder of the paper is organized as follows. In Section II, I present the models and develop the test hypotheses. Section III describes the data and the key variables. Section IV provides the empirical results. Section V checks the robustness. Section VI summarizes and draws conclusions.

II. The Model

In this section, I will first present the model with heterogeneous beliefs generated by investor overconfidence. The model with fully rational investors is developed as a special case of the overconfidence model in which the overconfidence level is set as zero. Although in this model overconfidence is used to create divergent beliefs between the irrational and the rational investors, the intuition potentially applies to other forms of irrationality.

The model setting is based on that of DHS (2001), which ties a factor model with both investor overconfidence and multiple securities to derive the relationship between cross-sectional dispersion of firm valuations and expected aggregate returns. In the model, There are two equally populated groups of risk averse investors, one rational, denoted as R, and the other overconfident, denoted as C.[13] Investors hold one riskless asset and N risky assets. There are three dates, $t = 0, 1, 2$. At date 0, investors start with their endowments and identical prior beliefs about the security payoffs. It is known to all investors that, at date 2, the riskless asset pays one unit per share and the risky asset pays θ_i, for all $i = 1, ..., N$. At date 1, investors receive an identical noisy private signal about the payoff of the common factor and exchange assets based on their beliefs. At date 2, the risky asset pays a liquidating dividend of θ and all consumption takes place.

Each risky asset has per capita supply of Q shares and its payoff at date 2 follows a

[13] The main conclusions of the model hold for any non-negligible fraction of overconfident population. As shown by DHS (2001), the equilibrium asset prices reflect the average overconfidence of investors. Thus, the assumption about the fraction of the overconfident population is not essential for deriving the main results.

single-factor structure:

$$\theta_i = \bar{\theta}_i + \beta_i F + \epsilon_i. \tag{1}$$

where $\bar{\theta}_i$ is the expected payoff of security i, ϵ_i is the firm-specific payoff, independently identically distributed as $N(0, 1/v^{\epsilon})$, and β_i is the loading of the ith security on the factor F. The common factor F is normally distributed as $N(0, 1/v)$. In addition, $E(F\epsilon_i) = 0$. The security loading, β, takes the values of β_1,..., β_N. I normalize the factor F to set the average β as one and denote cross-sectional variance of β as $\sigma^2(\beta)$. The values of $\bar{\theta}_i$, β_i, and the distribution of ϵ_i and F are common knowledge, but the realizations of ϵ_i and F are not known until date 2.

The noisy private signal about the common factor payoff at date 1 takes the form

$$S = F + e, \tag{2}$$

where e is the noise of the signal. It is normally distributed as $N(0, 1/v^R)$, where v^R is the true/rational precision of the signal. Overconfident investors mistakenly believe that the variance of the noise is lower, $1/v^C < 1/v^R$ (i.e., $v^C > v^R$). Thus, for overconfident investors, the mean and variance of the common factor payoff conditioning on the signals are given by:

$$\mu_C = \frac{v^C S}{v + v^C}, \quad \sigma_C^2 = \frac{1}{v + v^C}.$$

In contrast, for rational investors, the conditional mean and variance are given by

$$\mu_R = \frac{v^R S}{v + v^R}, \quad \sigma_R^2 = \frac{1}{v + v^R}.$$

In other words, overconfidence creates heterogeneous beliefs about the conditional distribution of future cash flows. The greater the overconfidence, measured by v^C, the greater divergence among investor expectations, defined as $l = \mu_C - \mu_R$.

After receiving the private signal, each investor selects her portfolio to maximize a CARA utility function with a risk aversion coefficient of A for date 2 consumption. Following DHS (2001), before I solve for the equilibrium price of individual securities, I first solve for the equilibrium price of the *factor portfolio*, which is constructed to have an expected payoff of zero and a loading of one on the common factor F. The equilibrium price of the factor portfolio is given by

$$P = \mu_{RC} - A\sigma_{RC}^2 Q, \tag{3}$$

where $\mu_{RC} = \gamma\mu_C + (1-\gamma)\mu_R = \mu_R + \gamma l$, $\gamma = \dfrac{\sigma_R^2}{\sigma_R^2 + \sigma_C^2}$, and $\sigma_{RC}^2 = \dfrac{2\sigma_R^2\sigma_C^2}{\sigma_R^2 + \sigma_C^2}$.

In equation (3), the first term is an weighted average expected factor cash flows of two investor groups. The second term is the price discount for risk, in which the conditional factor volatility is determined by the average perceived volatility of two investor groups. Due to the single factor payoff structure, the factor portfolio can also be defined as the market portfolio; therefore, the price of the market portfolio P_m is equal to P.[14]

Equation (3) suggests two distinct effects of overconfidence. First, overconfidence generates biased estimation of the expected cash flow. I define the factor cash flow mean bias (denoted as M) as the difference between investor expected factor cash flow and the true expected factor cash flow (i.e., $M = \mu_{RC} - \mu_R = \gamma l$). In other words, the mean bias M reflects l, the divergence in beliefs of two investor groups. Upon a favorable signal $S > 0$, the expected factor cash flow is overestimated ($M > 0$). Conversely, upon an adverse signal $S < 0$, the expected factor cash flow is underestimated ($M < 0$). Further, the magnitude of misestimation, defined as the absolute mean bias ($|M|$), increases as overconfidence (measured by v^C) rises. I call this the "mean bias effect."[15]

Second, overconfidence leads to lower perceived cash flow volatility. Since overconfident investors overestimate the accuracy of their signals, the average conditional cash flow variance is always smaller than the true variance ($\sigma^2_{RC} < \sigma^2_R$). Thus, given the true cash flow volatility, an average investor requires a smaller risk premium than the fully rational investors. I call this the "risk premium reduction effect."[16]

Later I will show that the combination of the mean bias effect and the risk premium reduction effect generate the negative relationship between firm valuation dispersion and expected aggregate returns. As an alternative approach, one can assume risk-neutral investors and additionally add short-sale constraints to produce the negative dispersion-return relationship.[17] However, incorporating risk aversion makes it convenient to derive the predictions from both risk and misvaluation under the same model framework and study the implication when both risk and mispricing are present.[18]

Let π denote the risk premium $A\sigma^2_{RC}Q$. Then the aggregate price P_m can be decomposed

[14]When N is large enough, the idiosyncratic risk is diversified away in the market portfolio.

[15]The misestimation effect causes price overreaction, excess volatility, and excess trading, which have been well established in previous overconfidence models (e.g. Odean (1998), Scheinkman & Xiong (2003)).

[16]It is worth noticing that this particular overconfidence effect is absent in most previous models due to the risk neutrality assumptions of investors (e.g., Odean (1998), DHS (1998), and Scheinkman & Xiong (2003)). The assumption of risk neutrality is usually invoked for tractability but at the expense of omitting the risk premium. As a result, these models only uncover the mean bias effect of overconfidence but fail to reveal the risk premium reduction effect.

[17]In this approach, the combination of heterogeneous beliefs and short-sale constraints lead to both greater firm valuation dispersion and low future market returns. In the one hand, firm valuation dispersion is greater when divergence in beliefs is larger. In the other hand, when short-sale constraints are binding, asset prices only reflect the beliefs of more optimistic investors, leading to overpricing and low future returns (Miller (1977)).

[18]My empirical tests do not distinguish whether the results are driven by risk aversion or short-sale constraints. As discussed previously, the main empirical predictions of the model are potentially compatible with combinations of other forms of investor irrationality and limits of arbitrage.

into three components: the true expected aggregate cash flow (μ_R), the cash flow mean bias (M), and the risk premium (π). Accordingly, equation (3) can be rewritten as

$$P_m = \mu_R + M - \pi. \tag{4}$$

Equation (4) shows that the aggregate price is high when the expected aggregate cash flow is high, the risk premium is low, or the expected cash flow is overestimated (M is more positive).

Let $E(R_m)$ denote the rational expected aggregate returns given private signals, defined as the difference between the true expected factor cash flow and the aggregate price. From equation (4), we have

$$E(R_m) = \pi - M. \tag{5}$$

That is, the expected aggregate return is determined by both risk premium and cash flow mean bias.

To derive firm valuation dispersion, note that, in equilibrium, asset i's price is determined by its unconditional expected cash flow and its cash flow sensitivity to the common factor.[19] That is,

$$P_i = \bar{\theta}_i + \beta_i P_m. \tag{6}$$

Let C_i be a noisy measure of the true expected cash flow of asset i conditional on the factor signal. Specifically,

$$C_i = \bar{\theta}_i + \beta_i \mu_R + \nu_i, \tag{7}$$

where ν_i is a firm-specific noise, independently identically distributed as $N(0, \sigma_\nu^2)$, and $E[\beta_i \nu_i] = 0$.[20] Empirically, C_i can be proxied by fundamental measures such as book equity, dividends, or earnings.

We measure valuation of asset i by $C_i - P_i$, which can be empirically proxied by the difference between logarithmic fundamental measures and logarithmic price. Combining equations (4), (6), and (7) yields a simple relationship between asset i's valuation and the market's valuation,

$$C_i - P_i = \beta_i E(R_m) = \beta_i(\pi - M) + \nu_i. \tag{8}$$

Taking the cross-sectional variance of both sides of equation (8) produces

$$\sigma^2(C - P) = \sigma^2(\beta)[E(R_m)]^2 = \sigma^2(\beta)(\pi - M)^2 + \sigma_\nu^2. \tag{9}$$

[19] This relationship can be easily derived from a non-arbitrage argument: since the payoff of asset i can be replicated by holding $\bar{\theta}_i$ units of the riskfree asset, β_i units of the market portfolio, and one unit of ϵ_i, the price of asset i should be equal to the sum of the prices of the three components in which ϵ_i is not priced since it is diversifiable.

[20] Alternatively, one can model C as a noisy measure of the true unconditional cash flow such that $C_i = \bar{\theta}_i + \nu_i$. This assumption leads to the same conclusion as the current model.

Since σ_ν^2 is a known constant, we can move it to the left-hand side of equation (11) and define the adjusted cross-sectional variance $\hat{\sigma}^2(C-P) = \sigma^2(C-P) - \sigma_\nu^2$. Thus, the adjusted firm valuation dispersion is[21]

$$\hat{\sigma}(C-P) = \sigma(\beta)\,|E(R_M)| = \sigma(\beta)\,|\pi - M|\,. \tag{10}$$

In equilibrium, both firm valuation dispersion and expected aggregate returns are endogenous. Thus, their relationship is usually determined by which exogenous variables are shifted. In the model based on overconfidence, we consider the shift in the overconfidence parameter, v^C. In the model with full rationality, we examine the shift in either investor risk aversion, A, or cash flow volatility, $1/v$.

We first consider the shift in overconfidence. Variation in overconfidence is consistent with findings from experimental studies of psychology. For example, it has been found that people tend to be more overconfident when individuals perform challenging judgment tasks (e.g., Lichtenstein, Fischhoff & Phillips (1982)), and when feedback is vague and deferred (e.g., Einhorn (1980)). Prior overconfidence models have studied the impacts of variation in overconfidence to some extent. For instance, Odean (1998) examines the effects of changes in overconfidence on volatility, price quality, and trading volume. Scheinkman & Xiong (2003) study its impacts on price bubbles, excess volatility, and trading frequency. Empirical evidence in finance also suggests that overconfidence is not constant.[22]

Through comparative statics, we have the following proposition:

Proposition 1. *As overconfidence v^C increases,*
1. If overconfidence is sufficiently strong ($v^C > v^{C'}$, where $v^{C'}$ is a constant), then on average the adjusted cross-sectional dispersion of firm valuations $\hat{\sigma}(C-P)$ increases; and
2. However, the expected aggregate return on average decreases.

[21] Equation (10) holds only when $\sigma(\beta)$ is non-zero, which is consistent with the empirical observation that there is a fairly large range of betas in the cross section (this observation is also verified in an unreported test by the author). However, when there is no cross-sectional dispersion in betas and when investors also receive signals about the idiosyncratic payoff ϵ, $\hat{\sigma}(C-P)$ would be a measure of cross-sectional dispersion in idiosyncratic returns. However, my results from the cross section of returns suggests that it should be cautious to interpret CVD as a measure of average idiosyncratic volatility. For example, I find returns on high beta stocks are more sensitive to the change in CVD than returns on low beta stocks, which suggests that CVD is unlikely to be solely associated with the idiosyncratic component of stock returns.

[22] For instance, using data from individual investor trading records, Kumar (2005) provides evidence that investor overconfidence changes with both stock-level and market-level information uncertainty. Zhang (2006) also finds that, consistent with the overconfidence hypothesis (Hirshleifer (2001)), a number of market anomalies are more pronounced among stocks with greater information uncertainty. In accordance to the overconfidence models of DHS (1998) and Gervais & Odean (2001), Statman et al. (2006) show that aggregate trading volume increases with past market returns, suggesting that overconfidence rises with good past investment outcomes.

See Appendix A for proof of all propositions.

Thus, in a sufficiently overconfident market, larger firm valuation dispersion *on average* should precede lower aggregate returns.

To obtain the intuition about the effects of overconfidence on firm valuation dispersion, let us consider two extreme cases. In Case 1, there is no risk premium ($\pi = 0$), and hence $\hat{\sigma}(C - P) = \sigma(\beta)\,|M|$. When overconfidence rises, the mean bias effect increases firm valuation dispersion. In Case 2, there is no mean bias ($M = 0$) and hence $\hat{\sigma}(C-P) = \sigma(\beta)\pi$. When overconfidence is stronger, the risk premium reduction effect reduces firm valuation dispersion.

That is, the mean bias effect and the risk premium reduction effect are two opposite forces driving firm valuation dispersion. But the two effects are not equally strong. In Appendix A, I show that the increase in the mean bias effect is faster than that in the risk premium reduction effect as overconfidence rises, due to the stronger effect of overestimation of signal precision on the conditional mean than on the conditional variance. Therefore, when overconfidence is sufficiently strong, the mean bias effect will dominate the risk premium reduction effect to determine firm valuation dispersion.

To understand the relationship between the average expected aggregate return and overconfidence, recall that the expected aggregate return conditional on private signals is $\pi - M$. On average, the expected aggregate return is equal to π because cash flow mean overestimation ($M > 0$) and underestimation ($M < 0$) are symmetric.[23] Thus, the upward bias and the downward bias are canceled out. As a result, the mean bias effect does not influence the average expected aggregate return. However, the risk premium π decreases with overconfidence due to the risk premium reduction effect. Therefore, the expected aggregate return is on average low when the overconfidence level is high.

In contrast, the variation in risk aversion or in factor cash flow volatility delivers an opposite prediction. When overconfidence is absent ($v^C = v^R$), the CAPM holds.[24] Since expectations are rational ($M = 0$), the adjusted firm valuation dispersion collapses to

$$\hat{\sigma}(C - P) = \sigma(\beta)\pi. \tag{11}$$

The above equation then leads to

Proposition 2. *As risk aversion A or factor cash flow volatility $1/v$ increases,*
1. The adjusted cross-sectional dispersion of firm valuation $\hat{\sigma}(C - P)$ increases; and
2. The expected aggregate return also increases.

[23]Since S is normally distributed with zero mean, cash flow misestimation is symmetric in both magnitude and probability. Thus, the unconditional mean of M is zero.

[24]DHS (2001) show that the unconditional CAPM holds when overconfidence is absent in their model.

Thus, if variation in expected returns is due to variation in rational risk premium, greater firm valuation dispersion should on average precede higher aggregate returns.[25] Intuitively, when risk aversion or factor cash flow volatility is high, the market risk premium is high, which increases both firm valuation dispersion and the expected aggregate return.

Taken together, Propositions 1 and 2 provide testable competing hypotheses; the overconfidence model predicts a negative dispersion-return relationship while the rational model predicts a positive relationship between the two.

In contrast, the relationship between the value spread and the expected aggregate return carries the same sign under the two models. Let the average beta of the value firms be β_v and that of the growth firms be β_g. When the number of firms in each group is sufficiently large, the value spread

$$(C - P)_v - (C - P)_g = (\beta_v - \beta_g)E(R_m). \tag{12}$$

Thus, the relationship between the value spread and the expected aggregate returns is determined by $\beta_v - \beta_g$ regardless whether the variation in the expected return is caused by variation in rational risk premium or in mispricing. A number of studies (e.g., Campbell & Vuolteenaho (2004)) find that the growth stocks on average have higher beta than the value stocks after 1963. Therefore, equation (12) predicts that the value spread should be negatively related to the expected aggregate return, a general finding in the value spread literature. However, this negative relationship between the value spread and expected aggregate returns does not help differentiate a behavioral theory from a rational theory.

Similarly, the aggregate valuation measure $C_m - P_m$ does not help to make this distinction, either. Let C_m denote the factor cash flow inferred from firm cash flows, i.e., the average $C_i - \bar{\theta}_i$. Given a sufficiently large number of assets, $C_m = \mu_R$ and hence,

$$C_m - P_m = E(R_m). \tag{13}$$

Thus, both the rational and the overconfidence models predict a positive relationship between the aggregate valuation measure and the expected aggregate return.

Furthermore, since β is a multiplier on the expected aggregate return, the two hypotheses have implications for the cross section of stock returns.

Proposition 3.
1. As overconfidence v^C increases, ceteris paribus, the reduction in the expected return of assets with higher betas is on average greater than that of assets with lower betas.

[25] In this model, $\sigma(\beta)$ is assumed to be constant. However, $\sigma(\beta)$ can be time-varying in a conditional CAPM. For example, the model in Gomes et al. (2003) implies that cross-sectional dispersion of beta should be positively correlated expected market returns, which is consistent with Proposition 2.

2. However, if investors are rational ($v^C = v^R$), as risk aversion A or factor cash flow volatility $1/v$ increases, the increase in the expected return of assets with higher beta is greater than that of assets with lower betas.

Thus, based upon the overconfidence model, the negative dispersion-return relation should be stronger among sets of high beta firms; when overconfidence reduces market risk premium, it should reduce the risk premium of high beta stocks more than that of low beta stocks. Following a similar reasoning, the rational model predicts that high beta stocks should exhibit a stronger positive dispersion-return relationship.

Taken together, I develop two sets of competing hypotheses.

Hypothesis I

a. (The risk hypothesis) Firm valuation dispersion should be *positively* related to subsequent aggregate stock returns.

b. (The misvaluation hypothesis) Firm valuation dispersion should be *negatively* related to subsequent aggregate stock returns.

Hypothesis II

a. (The risk hypothesis) The *positive* dispersion-return relation should be most pronounced among risky firms.

b. (The misvaluation hypothesis) The *negative* dispersion-return relation should be most pronounced among risky firms.

It is worth remarking that the two hypotheses are competing but not necessarily mutually exclusive. Observing a positive dispersion-return relationship in the data does not dispute the existence of market mispricing; it only suggests that risk is more important for understanding aggregate return predictability. Conversely, finding a negative relationship does not dispute the presence of risk; it only suggests that mispricing is present and has a stronger impact than risk on the dispersion-return relationship.

III. Data

The main sample includes all available firms listed in NYSE, AMEX, and NASDAQ from July 1963 to December 2004. Robustness checks also use the earlier period 1926–1962. Stock trading data are obtained from the Center of Research in Securities Prices (CRSP). Common stocks (share code 10 and 11) except those in the financial (SIC between 6000 and 6999) or the utilities (SIC between 4900 and 4949) are included. Accounting information is obtained from COMPUSTAT.

I calculate the cross-sectional standard deviations of three logarithmic firm valuation ratios: book-to-market equity (BM), dividend-to-price ratio (DP), and earnings-to-price ratio (EP), and denote them as σ(BM), σ(DP), and σ(EP). Both the value- and the equal-weighted measures are calculated. Book equity, dividends, and earnings as of December of year $t-1$ are used from June of year t to May of year $t+1$ and the end-of-month market equity or stock prices are used at the month of the calculation. The annual dispersion measures are computed at the end of each June. The quarterly dispersion measures are computed at the end of each March, June, September, and December. Firm book equity is calculated following Polk & Sapienza (2006). Market equity is the product of stock price and shares outstanding. Firm book-to-market equity (BM) is book equity over market equity. Firm dividend yield (DP) is total dividend payout over market equity. Firm earnings-to-price ratio (EP) is net income from continuing operation over market equity. Zero or negative book equity, dividends, and earnings are excluded to calculate logarithmic ratios.[26] I will focus my following description on the annual measures but the procedures and properties of the quarterly dispersion measures are similar to the annual ones.

——INSERT TABLE 1, 2 and FIGURE 1 HERE——

Panels A to C of Figure 1 plot the time-series of the annual dispersion variables. I find evidence of a quadratic time-trend in the value-weighted measures and a linear time-trend in the equal-weighted measures. The possible source of the time trend will be discussed later. Meanwhile, to purge out the influence of the time-trend on studying the serial correlation between dispersion and aggregate returns, along the line of Lo & Wang (2000), I regress each of the value-weighted measures on a time index (from 1 to 42 for annual measures and from 1 to 163 for quarterly measures), and the squared time index, and use the residuals as the detrended series. I also regress each of the equal-weighted measures on a time index and take the residuals as the detrended series. As shown in Table 2, the time trend does account for a substantial fraction of the time variation in these dispersion measures. The adjusted R^2s are 77% to 88% for the value-weighted measures and 32% to 77% for the equal-weighted measures. I denote the residuals from the above regressions as cd(BM), cd(DP), and cd(EP) and plot their time series on Figure 1. Finally, cross-firm valuation dispersion (CVD) is defined as the first principal component of cd(BM), cd(DP), and cd(EP). The summary statistics of all the measures are reported in Table 1.

——INSERT TABLE 3 HERE——

[26]Excluding the negative values results in a truncated distribution of firm valuation ratios, which might raise a concern about whether the truncation drives the results. As a robustness check, I use sales-to-price ratios to calculate firm valuation dispersion and still observe the negative correlation between dispersion and aggregate returns. Sales are usually positive and should include a more complete set of firms in my dispersion measure.

The same procedure is performed for the value-weighted measures and the equal-weighted measures separately. The procedures yield two parsimonious measures of the firm valuation dispersion that are constructed to have zero means and unit standard deviations:

$$\text{CVD}_{\text{vw}} = 0.357cd(\text{BM}) + 0.348cd(\text{DP}) + 0.347cd(\text{EP}), \qquad \text{and} \tag{14}$$

$$\text{CVD}_{\text{ew}} = 0.348cd(\text{BM}) + 0.396cd(\text{DP}) + 0.478cd(\text{EP}). \tag{15}$$

The value-weighted CVD explains 90% of the sample variance while the equal-weighted CVD explains 66%. For both measures, the first principal component is the only component with an eigenvalue greater than one and it is highly correlated with the underlying measures, as shown in Table 3.

The two CVDs have a high correlation of 0.75 and their time series are plotted in Panels G and H of Figure 1. The value-weighted CVD is positive for 1967–75, 1981, 1983, 1986–87, 1988–2001. Similarly, the equal-weighted CVD is also positive for 1967–75. However, the equal-weighted CVD behaves somewhat differently after 1980; it is positive for 1980–87, 1990–91, 1996, and 1999–2001. Both time series have a big spike in the post-1997 bubble period and reach their peak in 2000.

Returning to the time trend in σ(BM), σ(DP), and σ(EP), it is important to understand the source of the time trend to avoid potential data-mining. According to Campbell & Shiller (1988) and Vuolteenaho (2000), BM and DP contain not only a component of future returns but also a component of future growth rate. In particular, BM reflects the growth rate of book equity, the return on equity (ROE), while DP captures the growth rate of dividend payout (ΔD). Following a similar approach, I also show in Appendix B that EP is related to the growth rate of earnings (ΔE). Accordingly, cross-sectional dispersion in BM, DP, and EP should also reflect the dispersion in ROE, ΔD, and ΔE across firms.

—–INSERT FIGURE 2 HERE—–

As shown in Figure 2, the value- and equal-weighted dispersion measures of firm growth rates exhibit similar time trends to those in the valuation dispersion measures. This observation is also consistent with prior evidence that firm characteristics have become more dispersed nowadays than before.[27] Therefore, the time-trends in σ(BM), σ(DP), and σ(EP) are likely to be caused by time-trends in σ(ROE), $\sigma(\Delta$D), and $\sigma(\Delta$E) that are not captured in my models.[28] Thus, filtering the time trend does not change the insights of results to

[27] For example, firms going public have become younger (Fink, Fink, Grullon & Weston (2005)), and the dispersion of firm growth rates and that of profitability have become larger (Fama & French (2004)).

[28] In unreported tests, I also checked whether cross-sectional dispersion of the three firm growth rates can predict future aggregate returns and found no significant relationship. Thus, I conclude that the ability of CVD to predict future aggregate returns is not driven by any potential relationship between dispersion of growth rates and future returns.

distinguish the two hypotheses.

As an alternative approach, I also tried detrending the dispersion variables by subtracting its moving-average in the previous three to ten years. This method results in a similar detrended series for the equal-weighted dispersion measures. However, the value-weighted dispersion measures still exhibit a visible quadratic time trend. Nevertheless, I still find a significant negative dispersion-return relationship, although the results with respect to the value-weighted returns are weakened to some extent owing to the residual quadratic time trend. In addition, detrending with previous means leads to a loss of a few sample years. To make use of the full sample years to test my hypotheses, I report the main results based on dispersion measures detrended through regressions. To address further concerns about the detrending, I will discuss in Section V an alternative method that involves no detrending on the dispersion measures.

IV. Empirical Tests

A. CVD and aggregate indicators of heterogeneous beliefs and overconfidence

Under both the rational and the overconfidence models, CVD should be correlated with variables that capture business cycles and the time-varying risk premium. I will present the evidence later when discussing the correlations between CVD and other aggregate return predictors. Additionally, the model of overconfidence suggests that CVD should increase as overconfidence (or divergence in beliefs) becomes greater. Before testing the two competing hypotheses about the dispersion-return relationship, it is important to check whether CVD is related to overconfidence and heterogeneous beliefs at all.

As discussed previously, both theoretical and empirical research suggest that trading volume and idiosyncratic return volatility are associated with overconfidence and heterogeneous beliefs. Thus, we expect to see larger aggregate trading volume and higher aggregate idiosyncratic volatility when CVD is greater. The monthly aggregate trading volume (TURN_a) is calculated as the value- or equal-weighted average of monthly turnover ratios of all available firms, whereby turnover is the ratio of trading volume within the month over the end-of-month total shares outstanding.[29] The monthly aggregate idiosyncratic volatility (VOL_a) is the value- or equal-weighted average of firm idiosyncratic volatilities estimated through regressions of more than 17 daily returns on the FF 3 factors within the month (Ang, Hodrick, Xing & Zhang (2006)).

[29] Due to the double counting problem in NASDAQ (e.g., Atkins & Dyl (1997)), the trading volume from NASDAQ firms is divided by 2.

Consistent with prior literature (e.g. Campbell, Lettau, Malkiel & Xu (2001), Statman et al. (2006)), I find a (linear or quadratic) deterministic time trend in TURN_a and VOL_a. To examine the correlation between CVD and turnover or volatility that is independent from the time trend, I take out the time trend by regressing each of the variable in a deterministic (linear or quadratic) time index. I then examine the contemporaneous correlation between the levels and the innovations of CVD and those of TURN_a or VOL_a through regressions.[30]

—–INSERT TABLE 4 HERE—–

Shown in Panels A of Table 4, when the value- or equal-weighted TURN_a and VOL_a are regressed on CVD, the coefficients of CVD are all positive and statistically significant at the 1% level, suggesting that aggregate trading volume and idiosyncratic volatility tend to be high when CVD is high. Panel B reports the regression results of monthly changes in TURN_a (ΔTURN_a) and in VOL_a (ΔVOL_a) on monthly changes in CVD (ΔCVD). As can be seen, the coefficients of ΔCVD are positive and statistically significant at the 5% or the 10% level. Overall, the results suggest that firm valuations are highly dispersed when investors beliefs are more divergent.

In addition, prior literature suggests that overconfidence tends to grow after past trading success due to biased self-attribution (DHS (1998), Gervais & Odean (2001)). If CVD captures divergence in beliefs generated by overconfidence, we should expect an increase in CVD following a period of good past market returns. To test this conjecture, I regress the end-of-month value- or equal-weighted CVD on the prior 24 or 36 months CRSP index value-weighted returns. As reported in Panel C of Table 4, the coefficients on the past market returns are all positive and statistically significant, suggesting that CVD tends to be high after investors experience 2-3 years good stock market performance.

I also regress ΔCVD on past one-month and twelve-month market returns to assess whether high market returns shift overconfidence up. One month returns are chosen because the regression is at the monthly frequency. Twelve-month returns are chosen because Benartzi & Thaler (1995) suggest that a reasonable evaluation period for an average investor should be around 12 months in order to explain the observed average asset allocation. As can be seen from Panel D, the coefficients of past 12-month market returns are all positive and mostly statistically significant, suggesting that firm valuation dispersion increases after one-year good performance of the stock markets.

Overall, the evidence suggests that firm valuation dispersion is also likely to capture heterogeneous beliefs of investors generated by overconfidence.

[30]The correlation results are consistent with with the regression results.

B. Forecasting aggregate returns

Having confirmed that CVD captures both business cycles and investor heterogeneous beliefs, I proceed to test whether it is risk or misvaluation that dominates the relationship between CVD and subsequent aggregate returns.

1. Sorts

To test Hypothesis I, I first examine the aggregate return patterns conditioning on beginning-of-period CVD. The CRSP value-weighted and equal-weighted index returns from 1963 to 2005 are used as aggregate stock returns. Based on whether the end-of-June CVD is above the mean (zero) or below the mean, I sort the subsequent three consecutive 12-month continuously-compounded market excess returns. Shown in Figure 3, during the full sample period, when CVD is relatively low, the average 12-month value-weighted market excess returns are around 7–8% in the following three years. In contrast, when CVD is relatively high, these excess returns are abysmal and even negative in the subsequent three years, ranging from −0.49% to −1.15% per annum. The negative premium is at odds with the rational view that risk premium should never be negative.

Equal-weighted market excess returns exhibit similar patterns. Following low CVD periods the annual market excess returns are 10–15%, while following high CVD periods these excess returns are merely 2–6%. Apparently, the sorts suggest a negative relationship between dispersion and subsequent aggregate returns, which confirms the prediction from the overconfidence model.

—–INSERT FIGURE 3 HERE—–

To make sure the poor performance following high CVD period is not solely driven by the post-1997 bubble period, I conduct sorts based on CVD from 1963 to 1996 and report the results in Figure 3. The return patterns conditioning on CVD remain unchanged. During this sample period, following high CVD, the one-year market performance is even worse; the average value-weighted annual return is only −4.52%. Thus, these results suggest that the negative relationship between CVD and future market excess returns is also present before 1997.

2. Univariate regressions

To formally evaluate the predictive power of CVD, I regress market excess returns on lagged CVD. The value-weighted (equal-weighted) CVD is used to predict value-weighted (equal-weighted) returns. I report results on three different return horizons: one quarter, one year, and three years. The results for other return horizons from 1 month to 3 years are qualitatively similar. For one-quarter-ahead returns, the predictors are updated at the end of each March, June, September, and December. For one-year-ahead or three-year-ahead returns, they are updated annually at the end of each June. Overlapping observations are used for the three-year return regressions. The OLS coefficients and R^2 are reported. Since the OLS t-statistics may be subject to the small sample bias (Stambaugh ((1986, 1999)), I report the one-tail p-value based on the simulated distribution of the predictive slope following Nelson & Kim (1993).[31]

—–INSERT TABLE 5 HERE—–

Panel A of Table 5 reports the results with the full sample and Panel B reports the results after excluding the post-1997 period. As can be seen, the coefficients of CVD are all negative and significant at the 5% level.

The economic magnitude of the impact of CVD on aggregate returns is large. For the value-weighted market excess returns, in the full sample a one standard deviation positive shock to CVD results in a 2.38% reduction in subsequent 1-quarter returns, a 8.34% reduction in subsequent one-year returns and a 18.97% reduction in subsequent three-year returns.[32] The three coefficients of CVD are 2.58%, 8.76% and 12.74% using the equal-weighted market excess returns. As reported in Panel B of Table 5, all CVD coefficients remain negative and highly significant. Excluding the post-1997 period yields similar results.

In sum, the results are consistent with the misvaluation hypothesis that CVD is negatively related to future market excess returns. The results are inconsistent with the risk hypothesis which predicts a positive relationship between CVD and subsequent aggregate returns.

3. Multivariate regression

Previous studies have identified a number of predictors of market returns. Some of the well-known ones include dividend yields (D/P) (Campbell & Shiller (1988), Fama & French (1988*a*), Lewellen (2004)), short-term interest rates (Fama & Schwert (1977)), past market

[31] Stambaugh points out that the OLS estimator in a predictive regression will be biased to favor the alternative in a small sample if (1) the regressor is highly persistent and (2) the innovation of the predicted variable and that of the forecaster are correlated. Shown in Table 1, the first-order autocorrelation of CVD is 0.58 in the value-weighted scheme and 0.44 in the equal-weighted scheme, suggesting CVD is relatively persistent. Furthermore, preliminary analyses find that shocks to the expected market returns are correlated with shocks to CVD. Thus, the bias is likely to be present. For convenience, the one-tail p-values reported in this paper are adjusted to be less than 0.5. That is, if the simulated p-value is greater than 0.5, indicating that the estimated coefficient is in the right tail of the simulated distribution, the reported p-value is equal to one subtracted by the estimated p-value.

[32] Since CVD has unit variance by construction, the coefficients measure the effect of a one standard deviation shock to CVD on expected returns.

returns (Fama & French (1988*b*)), the default and term premium (Fama & French (1989)), the aggregate relative equity issuances (Baker & Wurgler (2000)), and the consumption-wealth ratio (*cay*) (Lettau & Ludvigson (2001)). Although the main focus of this paper is not to propose a new aggregate return predictor, it is still interesting to examine whether CVD provides incremental power to forecast future aggregate returns.

Aggregate dividend yields (D/P) are computed following Fama & French (1988*a*). Annual dividends are used to avoid seasonal differences in dividend payments. Short term interest rates (TBILL) are measured by the one-month treasury bill rates obtained from Ibbotson Associates. Past market return (Rm) is the past return on the value-weighted CRSP index. Following Fama & French (1988*b*), past six-month, one-year, and three-year market returns are used, respectively, to forecast market returns six months, one year, and three years ahead. The aggregate relative equity issuance variable (S) is obtained from Wurgler's website over the period 1962–2002. Term premium (TERM) is defined as the difference between the 10-year treasury constant maturity rate and the one-year treasury constant maturity rate. Default premium (DEF) is defined as the difference between the Moody's seasoned Aaa corporate bond yield and the Moody's seasoned Baa corporate bond yield. The yield data are obtained from the Federal Reserve System website.[33] The consumption-wealth ratios (*cay*) are obtained from Martin Lettau's website over the period 1951–2003.

The correlations of these predictors and CVD are reported in Panel C of Table II, which shows that the value-weighted CVD has a significant negative correlation with D/P, TERM, and DEF and the equal-weighted CVD has a significant positive correlation with TBILL. Interestingly, both dispersion measures have significant negative correlations with *cay*. The correlations between CVD and business cycle proxies such as TERM and DEF are not surprising. As shown in the models, CVD is affected by expected market returns, which are influenced by business cycle and economic conditions. However, if the variation in CVD is solely determined by business cycle and economic conditions, we would expect to observe a positive correlation between CVD and future market returns.

—–INSERT TABLES 6 HERE—–

Table 6 reports the regression results of the value-weighted aggregate excess returns on the set of predictors. For each of the three return horizons, four regressions are run. Two of them only include the well-known predictors, one with and one without *cay*. The other two also include CVD to assess its incremental power to predict returns.

As can be seen, CVD remains significantly negative at all three return horizons when added to the set of standard predictors (excluding *cay*). The CVD coefficients remain similar

[33] In a robustness check, I also use the term premium and the default premium obtained from Ibbotson Associates over the period 1963–1999. The main results remain unchanged.

in magnitude to that when it is used alone. CVD also increases the ability to forecast future value-weighted equity premium. It tends to double or triple the explained variance of the future aggregate returns across the three horizons.

When *cay* is included as an additional control CVD remains negative, however, the incremental power of CVD differs across return horizons. In forecasting one-quarter-ahead returns, *cay* diminishes the power of CVD: CVD becomes insignificant and does little to improve the R^2. In contrast, when one-year-ahead returns are forecasted, CVD makes *cay* insignificant. In the three-year return regression, both CVD and *cay* remain in the expected signs and statistically significant, suggesting that CVD and *cay* are complementary in forecasting long-horizon returns.

The results with equal-weighted market excess returns, reported in Panel B of Table 6, are qualitatively similar to those with value-weighted returns. Overall, the results with both value-weighted and equal-weighted schemes suggest that CVD provides incremental information about expected market returns over and above these well-known predictors, particularly for the value-weighted returns and long horizon returns.

4. Alternative measures of dispersion

Related to the previous discussion, a few studies have proposed several measures of spreads among valuation ratios, including the value spread (Cohen et al. (2003)), the book-to-market (BM) spread, and the market-to-book (MB) spread (Liu & Zhang (2007)), where the BM (MB) spread is the difference of book-to-market (market-to-book) equity between the two classes of stocks. My model has shown that the key difference between CVD and the value spread is that the former helps to differentiate two competing hypotheses while the latter does not. However, it is still interesting to compare the forecasting power of CVD with that of the value spread and the other spreads.

—–INSERT TABLE 7 HERE—–

I regress market excess returns in three horizons, respectively, on the BM spread, the MB spread, the value spread, and the small value spread with and without CVD and report the results in Table 7. In calculating the BM spread, the MB spread, and the value spread, I follow Liu & Zhang (2007) to define value firms and growth firms as the top and the bottom BM deciles. The quarterly series of the small value spread is from Campbell & Vuolteenaho (2004) over the period 1963–2001.[34]

[34] I also calculated the small value spread following Campbell & Vuolteenaho (2004) over the period 1963–2004. The results remain qualitatively similar.

As shown in Table 7, over my sample period, CVD is a stronger predictor than any of the valuation spread measures. When used alone, the MB spread and the small value spread have a significant coefficient in predicting both equal-weighted and value-weighted returns, and the BM spread predicts the equal-weighted returns. However, adding CVD in general diminishes the power of these spread measures to forecast returns; most of them become insignificant and some of them switched signs. In contrast, CVD remains negative in general statistically significant.[35] Therefore, the results suggest that CVD is more helpful in predicting returns than the spread measures.

C. Forecasting portfolio returns

Tests of Hypothesis I uncover a strong negative relationship between CVD and subsequent aggregate returns and suggest that misvaluation is the dominate force in driving the dispersion-return relationship. I proceed to test Hypothesis II, which predicts a stronger CVD-return relationship among riskier stocks.

For measures of risk, I use market beta (BETA) and total return volatility (VOL). BETA is estimated from a market model on 36 to 60 monthly available returns in the 5 years before July of year t.[36] VOL is the standard deviation of 10 to 12 monthly returns before July of year t (Nagel (2005)). After excluding stocks with prices less than \$5 (e.g., Jegadeesh & Titman (2001)), I form the BETA quintiles based on the breakpoints of NYSE firms and the VOL quintiles based on the breakpoints of all available firms. Changing the breakpoints or including low price stocks do not materially change the results. The annual returns are continuously-compounded value-weighted monthly returns from July of year t to June of year $t+1$. Based on the overconfidence hypothesis, I expect a stronger negative dispersion-return relation among sets of firms that have larger beta or greater return volatility. In contrast, based on the risk hypothesis, I expect a stronger positive dispersion-return relation among these sets of firms.

[35]The only occasion that CVD is not significant in when it is competing against the small value spread in forecasting one-year-ahead equal-weighted returns. In this regression, the small value spread also becomes insignificant.

[36]The reported results are based on the betas that are estimated from the time-series regression $R_{i,t} = \alpha + \beta_i R_{MKT,t} + \nu_i$. To account for the effects of nonsynchronous trading, I also estimate betas from the regression $R_{i,t} = \alpha + \beta_{i,1} R_{MKT,t-1} + \beta_{i,2} R_{MKT,t} + \nu_i$ and define $\beta_i = \beta_{i,1} + \beta_{i,2}$ (e.g., Fama & French (1992), Lewellen & Nagel (2005)). The main results still hold.

1. Predicting portfolio returns using CVD

I first regress the annual returns on each of the BETA or VOL quintiles on the equal-weighted CVD and then look for the cross-sectional patterns of the CVD coefficients.[37] Panel A of Table 8 reports the results for each of the quintiles as well as the the hedging portfolios that are long on the lowest BETA or VOL quintile and short on the highest BETA or VOL quintile.

Consistent with the misvaluation hypothesis, the coefficients of CVD are all negative, and they are the most negative for the highest BETA or VOL quintile and the least negative for the lowest BETA or VOL quintile. The fraction of the explained return variation is also the greatest among the riskiest stocks and the smallest among the least risky stocks. The CVD coefficient on the long-short BETA portfolio is 13.57, suggesting that a one-standard-deviation increase in CVD on average reduces the highest beta quintile returns by 13.57% per annum more than that of the lowest beta quintile returns. And the CVD coefficient on the long-short VOL portfolio is 17.62, representing even a greater impact of CVD on the cross section of VOL quintile returns.

———INSERT TABLE 8 HERE———

Although CVD is shown to distinctively influence firms with different beta or volatility, it is possible that the differences in sensitivity are only due to differences in firms' exposure to other systematic risk factors. Therefore, I run the predictive regressions by adding multiple contemporaneous risk factors. I consider three multifactor models: the 3-factor model (Fama & French (1993)), the 4-factor model (Carhart (1997)), and the ICAPM of Brennan et al. (2004). The first two models are empirically motivated while the last one stems from theory.

With respect to the 3- or the 4-factor models, there has been a debate on whether the size factor (SMB), the book-to-market factor (HML), and the momentum factor (UMD) proxy for risk or mispricing.[38]. Therefore, these factors, if related to mispricing, can possibly drive out the power of CVD to predict returns. Nonetheless, as long as CVD captures more misvaluation than these factors, the lagged CVD should continue to forecast portfolio returns even after controlling for these contemporaneous factors. In that case, these kinds of tests can at least distinguish whether CVD picks up novel effects beyond the well-known comovement in stock returns.

[37] I find that the time-variation in the value-weighted CVD is mostly driven by the largest 5% stocks. Prior literature (e.g., Fama & French (1992)) find that beta is negatively correlated with firm size. Thus, when examining the correlation between beta quintile returns and CVD, using the equal-weighted CVD as a common predictor across the quintiles helps to void the mechanical relationship among low beta (and also large) stocks.

[38] Among others, Fama & French (1995), Daniel & Titman (1997), and Daniel, Hirshleifer & Subrahmanyam (2005).

Specifically, I run the following time series regressions for each of quintiles and the long-short portfolios, a method used by prior studies (e.g., Lewellen (1999), Baker & Wurgler (2006)).

$$R_t = c + d\mathrm{CVD_{t-1}} + \beta\mathrm{MKT_t} + s\mathrm{SMB_t} + h\mathrm{HML_t} + u_t, \tag{16}$$

$$R_t = c + d\mathrm{CVD_{t-1}} + \beta\mathrm{MKT_t} + s\mathrm{SMB_t} + h\mathrm{HML_t} + m\mathrm{UMD_t} + u_t, \tag{17}$$

$$R_t = c + d\mathrm{CVD_{t-1}} + \beta\mathrm{MKT_t} + b\Delta\gamma_\mathrm{t} + e\Delta\eta_\mathrm{t} + u_t, \tag{18}$$

where MKT is the market excess returns, $\Delta\gamma$ is the estimated innovation in the instantaneous real interest rate, and $\Delta\eta$ is the estimated innovation in the instantaneous market Sharpe ratio. Regression (16) controls for the FF 3 factors, Regression (17) controls for the 4 factors, and Regression (18) controls for the innovations in the two state variables in addition to the market factor in the BWX ICAPM. The time series from 1963 to 2004 of the FF 3 factors and the momentum factor are obtained from French's website. The time series of both $\Delta\gamma$ and $\Delta\eta$ are obtained from Yihong Xia's website, which is available until the end of 2001.

Panels B, C, and D in Table 8 report the results. It can be seen that the three specifications yield similar results. The CVD coefficients turn positive among quintiles with relatively lower BETA or VOL and remain negative among quintiles with relatively higher BETA or VOL. Nevertheless, the CVD coefficients for the long-short BETA and VOL portfolios all remain negative and statistically significant, suggesting a greater impact of CVD on riskier stocks even in the presence of contemporaneous common factors. Thus, the cross-sectional differences in the return sensitivities with respect to CVD are not fully explained by the cross-sectional differences in portfolios' exposure to a set of known factors.

2. Two-way sorts

To further examine the cross-sectional return patterns conditioning on CVD, I conduct two-way sorts following Baker & Wurgler (2006). Stocks are first sorted into BETA or VOL quintiles as described previously. Then the BETA and VOL quintiles are sorted into two states based on the end-of-June CVD of year t. In one state, CVD is above the full sample mean (CVD > 0) while in the other CVD is below the full sample mean (CVD < 0).[39] Based

[39] According to Baker & Wurgler (2006), the two-way sorts help uncover the cross-sectional return patterns in the sample. However, since it involves using the full sample information to conduct the sorts, the long-short strategies presented in Table 9 are not exploitable *ex ante*. To evaluate the validity of the long-short strategy, I also conduct sorts based on the sign of the changes in raw dispersion measures (undetrended) relative to its moving average in the past one to three years, and find qualitatively similar results. In particular, the results with changes relative to the 3 years moving average are quantitatively similar. This alternative method involves only prior information to form the long-short portfolios and suggest that the results in Table 9 are not due to the use of the full sample information.

on the misvaluation hypothesis, the reduction of returns from the low to the high CVD state should be greater among riskier stocks.

—–INSERT TABLE 9 HERE—–

The two-way sort results are reported in Table 9. Indeed, when moving from the low to the high CVD state, the return reduction monotonically changes across the quintiles; the reduction is the greatest among the highest BETA or VOL quintile and the smallest among the lowest BETA or VOL quintiles. More interestingly, we see opposite return patterns across the two CVD states. During the low CVD states, the highest beta quintile *overperform* the lowest beta quintile by 7.02% per annum. In contrast, during the high CVD states, the highest beta quintile *underperform* the lowest beta quintile by 7.09% per annum. Similarly, the return differential between the highest volatility quintile and the lowest volatility quintile is 12.33% per annum during low CVD periods but merely −9.77% per annum during high CVD periods.

In other words, when the beginning-of-period CVD is relatively low—suggesting less divergent investor beliefs and smaller aggregate misvaluation, the cross section of return patterns reflect a positive risk-return trade-off. In contrast, when the beginning-of-period CVD is relatively high—indicating greater disagreement among investors and larger aggregate misvaluation, the cross section of returns show an anomalous negative risk-return trade-off. The evidence is consistent with the overconfidence model: when overconfidence is sufficient strong, misvaluation dominates risk and riskier stocks share more common misvaluation and earn lower returns; conversely, when overconfidence is relatively weak, risk dominates misvaluation in determining expected returns and investors are rewarded higher return by holding riskier positions.

V. Robustness

In assessing the robustness of the empirical findings, I focus on three issues. First, in order to evaluate the performance of CVD in another time period, I run the predictive regression from 1926 to 1962. Second, to further address the concern about the detrending method, I examine the forecast power of the undetrended dispersion measures together with time indices. Third, I study the sensitivity of the results by considering changes in firm composition in the dispersion measures.

The previous results have focused on the period 1963–2004. Thus, the earlier period 1926–1962 can serve as an additional sample of the empirical performance of CVD. Since earnings data at the firm level are not directly available for the pre-1963 period, I construct CVD from the dispersion in book-to-market equity and in dividend-to-price ratios. I first calculate both the value-weighted and the equal-weighted σ(BM) and σ(DP) at the end of each June. Firm book equity data is obtained from French's website. Firm dividend payout is constructed from CRSP stock returns with and without distribution (e.g., Fama & French (1988*a*)). Similar to the time series of the dispersion variables after 1963, I find a quadratic time trend in the value-weighted measures and a linear time trend in the equal-weighted measures. Thus, I detrend these variables accordingly through regressions and denote the detrended variables as *cd*(BM) and *cd*(DP). Finally, CVD is defined as the principal component of *cd*(BM) and *cd*(DP) during this period.

———INSERT TABLE 10 HERE———

I report in Table 10 the regression results of future one-year and three-year market excess returns on each of the three predictors: CVD, *cd*(BM), and *cd*(DP). Consistent with the earlier results, CVD exhibits a strong negative relationship with the subsequent value-weighted market excess returns. Similar results are present using *cd*(BM) and *cd*(DP). However, in forecasting the equal-weighted market excess returns, CVD remains negative but becomes insignificant, which, shown in Panel B, is due to a weak relationship between *cd*(BM) and subsequent equal-weighted aggregate returns. In contrast, the coefficients on *cd*(DP) are all negative and highly significant. Nevertheless, the results show that firm valuation dispersion is negatively related to subsequent value-weighted market excess returns over 1926–1962.

Second, in the above tests, CVD is constructed from residuals by regressing the full-sample firm valuation dispersion on a time index. This might raise a concern about "look-ahead bias" (Brennan & Xia (2005)), which refers to strong forecasting power due to "ex post successfully fitting of the trend within the sample." To address this concern, I define CVD_{raw} as the first principal component of σ(BM), σ(DP), and σ(EP), none of which is detrended. Then I regress market excess returns on lagged CVD_{raw} together with a time index (t-index) (and the squared time index, t^2-index, for the value-weighted returns).[40] This method requires only prior information at each point of time to forecast returns in the sample and is used by Lettau & Ludvigson (2005) to address the possible look-ahead bias raised by Brennan and Xia. A significant CVD coefficient in this regression will confirm that the forecast power of CVD is not driven by the ex post detrending.[41]

[40] As shown in Table 2, the value-weighted raw valuation dispersion measures exhibit a quadratic time trend, consistent with the time trend in the value-weighted dispersion in growth rates in Figure 2. The equal-weighted raw valuation dispersion measures have a linear time trend, similar to the trend in the equal-weighted dispersion in growth rates.

[41] Of course, this type of test, as other typical in-sample predictive regressions, does not help to evaluate the out-of-sample performance of the predictors in predicting returns in the future.

———INSERT TABLE 11 HERE———

The results of forecasting one-year and three-year return are reported in Table 11. The coefficients on CVD_{raw} are all negative and highly significant. Confirming the existence of a quadratic time trend in the value-weighted CVD_{raw}, the coefficients on both t-index and t^2-index are statistically significant. Also consistent with a linear time trend in the equal-weighted CVD_{raw}, t-index is significant. Finally, The R^2s are similar to those when CVD is used as a sole predictor. Thus, the results show that the undetrended firm valuation dispersion and time indices jointly forecast aggregate stock returns, suggesting that the look-ahead bias is not responsible for the ability of CVD to predict aggregate returns.

Finally, I explore whether my results are explained by changes in firm composition instead of by changes in existing firms' valuations. Firm valuation dispersion can become larger when the existing firms' valuations are more dispersed. Alternatively, greater dispersion can occur when newly listed firms have extreme valuations. To examine whether the negative dispersion-return relationship holds for existing firms, I collect a group of firms that appear in my sample every year from 1965 to 2004. I then calculate CVD for this group of firms and find that CVD still negatively and significantly forecasts subsequent returns of this portfolio.[42] Thus, I conclude that the change in firm composition is not responsible for my empirical results.

VI. Summary and Conclusion

Over the past two decades finance academia has seen the discovery of many return predictors. As evidence of stock return predictability mounts the desire to more clearly understand predictability has increased as well. This paper attempts to contribute to the growing body of literature by not only documenting the predictability, but helping to understand it.

I find that, over the period 1963–2004, cross-sectional dispersion of firm valuations is a negative predictor of subsequent market and portfolio excess returns up to three years ahead. This predictability is most pronounced among firms with large beta and high return volatility. More interestingly, I observe a positive relationship between beta/volatility and the cross section of stock returns when the beginning-of-period firm valuation dispersion is relatively low. In contrast, the beta/volatility has a negative relationship with the cross section of returns when dispersion is relatively high.

[42] I also limit my sample firms to the largest size quintile, the largest age quintile, or the highest BM quintile, and calculate dispersion only based on firms in that quintile, and still observe a negative correlation between CVD and subsequent portfolio returns. These quintiles include more mature firms and are less likely to be heavily influenced by new issues.

Through two pricing models, I show that the empirical results can be understood in a market with heterogeneous beliefs and aggregate mispricing, and these results are less likely to occur based on full rationality and the discount rate effect. Thus, dispersion helps to differentiate risk from mispricing while the aggregate fundamental-to-price ratios and the value spread do not.

Although heterogeneous beliefs in my model are created by investor overconfidence, the intuition for the negative dispersion-return relation can be applied for combinations of other forms of investor irrationality and limits of arbitrage. In contrast, few existing theories based solely on risk can fully explain the empirical findings in this paper. For example, the model of Brennan et al. (2004) implies that firm valuation dispersion captures the absolute value of the state variable. However, it is unclear why high dispersion should on average forecast low future aggregate returns. It is also puzzling that the ICAPM of Brennan et al. (2004) does not fully explain the cross-sectional differences in the predictive power of CVD, my measure of firm valuation dispersion. Another possibility is that CVD may proxy for the uncertainty about firm cash flow growth rates (e.g., Pastor & Veronesi (2003)). However, this literature has no implication for the predictability of the equity premium.

Nevertheless, the empirical relationships between CVD and the aggregate trading volume, the aggregate idiosyncratic volatility, the past and future aggregate returns, together with the cross-sectional return patterns across the high and low dispersion states, are interesting by themselves, regardless of one's interpretation. Future research may consider developing models based on risk to explain the empirical findings in this study and to provide further testable implications.

Appendix A: Proofs

Proof of Proposition 1

Since $\sigma(\beta)$ is a constant, for brevity, I assume that it is equal to one in all proofs. Thus,

$$\begin{aligned} E[\hat{\sigma}(C-P)] &= \int_{-\infty}^{S^*} (\pi - M) f(S) dS + \int_{S^*}^{+\infty} (M - \pi) f(S) dS \\ &= \int_{-\infty}^{S^*} \pi f(S) dS - \int_{S^*}^{+\infty} \pi f(S) dS + \int_{S^*}^{+\infty} M f(S) dS - \int_{-\infty}^{S^*} M f(S) dS, \end{aligned}$$

where $S^* = 2AQ\dfrac{v + v^R}{v(v^C - v^R)}$ and $M(S^*) = \pi$. When S is above S^* or below $-S^*$, $|M| > \pi$, the mean bias effect dominates the risk premium reduction effect in determining firm valuation dispersion. Conversely, when S is between $-S^*$ and S^*, $\pi > |M|$, the risk premium reduction effect dominates.

Further, let $\omega = 1/(2v + v^C + v^R)$, and $M^* = M(S^*)$, taking derivative with respect to v^C yields

$$\begin{aligned} \frac{\partial E[\tilde{\sigma}(C-P)]}{\partial v^C} &= -\omega\pi \left[2F(S^*) - 1\right] + 2\frac{\partial S^*}{\partial v^C}\pi f(S^*) - 2\frac{\partial S^*}{\partial v^C} M^* f(S^*) \\ &+ \int_{S^*}^{+\infty} v\omega^2 S f(S) dS - \int_{-\infty}^{S^*} v\omega^2 S f(S) dS \\ &= v\omega^2 \left\{ \int_{S^*}^{+\infty} S f(S) dS - \int_{-\infty}^{S^*} S f(S) dS - \frac{2AQ}{v}\left[2F(S^*) - 1\right] \right\} \end{aligned}$$

If this derivative is greater than zero, then that in brace must be positive since $v\omega^2$ is positive. All else equal, this inequality becomes more likely to hold when overconfidence is strong.

To see that this derivative is positive when v^C is large enough, let us denote the component in brace as Ω, and taking derivative on Ω with respect to v^C yields

$$\frac{\partial \Omega}{\partial v^C} = -2f(S^*)\frac{\partial S^*}{\partial v^C}\left(S^* + \frac{2AQ}{v}\right) > 0,$$

since $\dfrac{\partial S^*}{\partial v^C} < 0$. Thus, Ω becomes larger when v^C is larger. Consider two extreme cases. In Case 1, overconfidence is extremely low such that v^C approaches v^R. Then S^* approaches infinity and Ω is negative. In Case 2, overconfidence is extremely strong such that v^C approaches infinity. Then S^* approaches zero and Ω is positive. Thus, there must exist a threshold $v^{C'}$ $(0 < v^{C'} < +\infty)$, above which Ω is positive. □

Proof of Proposition 2

Let $v^C = v^R$ so there is no overconfidence, the CAPM holds in this model. The expected aggregate return is equal to the market risk premium, i.e., $\pi = A\sigma^2_{RC}Q$. It is easy to show that

$$\frac{\partial \pi}{\partial A} = \sigma^2_{RC}Q > 0, \qquad \frac{\partial \pi}{\partial (1/v)} = 2v^2\pi\omega > 0.$$

That is, when the risk aversion A or the factor cash flow volatility is greater (v is smaller), the risk premium π is greater. Since the expected aggregate return is equal to π and $\hat{\sigma}(C - P) = \sigma(\beta)\pi$, greater risk premia lead to both higher expected aggregate return and larger $\hat{\sigma}(C - P)$. □

Proof of Proposition 3

Suppose there are two assets that have market betas of β_1 and β_2, respectively, and $\beta_1 > \beta_2$. Then the average expected returns are $\beta_1\pi$ and $\beta_2\pi$. Hence, for a unit increase in overconfidence v^C, the average expected return on asset one is reduced by $\beta_1 \left|\frac{\partial \pi}{\partial v^C}\right|$ while that on asset two is reduced by $\beta_2 \left|\frac{\partial \pi}{\partial v^C}\right|$. Thus, the return reduction effect of overconfidence is stronger among asset one. □

Appendix B. Decomposition of earnings-to-price ratio

Let D be the dividend per share, E be the earnings per share, P be the stock price, d be the log dividend per share, e be the log earnings per share, p be the log price. Further, let δ denote the log earnings-to-price ratio, θ be the log dividend-to-earnings ratio, and Δe be the log earnings growth rate. Let r denote the log stock return, defined as

$$r_t = \log\left(\frac{P_t + D_t}{P_{t-1}}\right). \tag{B-1}$$

Substituting δ, θ, and Δe into equation (B-1) yields

$$r_t = \Delta e_t + \delta_{t-1} + \theta_t + \log(\exp(-(\delta_t + \theta_t))). \tag{B-2}$$

I approximate the stock returns by a first-order Taylor expansion and obtain

$$r_t = \Delta e_t + \delta_{t-1} + \theta_t - \rho(\delta_t + \theta_t) + \kappa_t.$$

where ρ is a parameter and κ is an approximation error plus a constant. If the firm pays any dividends then $\rho < 1$, and otherwise $\rho = 0$. Rearranging the terms yields

$$r_t - \Delta e_t - (1 - \rho)\theta_t = \delta_{t-1} - \rho\delta_t + \kappa_t. \tag{B-3}$$

Using the linear form in equation (B-3), I iterate forward and express the EP ratio as an infinite discounted sum of future returns less future earnings growth rates and future dividend payout ratios:

$$\delta_{t-1} = \sum_{j=0}^{\infty} \rho^j r_{t+j} + \sum_{j=0}^{\infty} \rho^j (-\Delta e_{t+j}) + \sum_{j=0}^{\infty} \rho^j (\rho - 1)\theta_{t+j} + \sum_{j=0}^{\infty} \kappa_{t+j}. \tag{B-4}$$

If we further assume the dividend payout ratio is a constant, then

$$\delta_{t-1} = \sum_{j=0}^{\infty} \rho^j r_{t+j} + \sum_{j=0}^{\infty} \rho^j (-\Delta e_{t+j}) + \sum_{j=0}^{\infty} \kappa'_{t+j}. \tag{B-5}$$

The above decomposition shows that the log earnings-to-price ratio is approximately the sum of future returns less future earnings growth rates plus a constant.

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Table 1: Summary statistics of the dispersion variables

This table reports the descriptive statistics of the annual dispersion variables over the period 1963–2004, including the number of observations (Obs), the time series mean (Mean), the time series standard deviation (Std), the maximum (Max), the minimum (Min), and the autocorrelations in three lags. Each variable is formed based on all available firms in NYSE, AMEX, and NASDAQ. Variables in Panel A are in a value-weighted scheme and those in Panel B are in an equal-weighted scheme. The variables σ(BM), σ(DP), and σ(EP) are, respectively, the cross-sectional standard deviation of logarithmic firm book-to-market equity, dividend-to-price ratios, and earnings-to-price ratios. The variables cd(BM), cd(DP), and cd(EP) are the detrended σ(BM), σ(DP), and σ(EP). The variable CVD is the first principal component of cd(BM), cd(DP), and cd(EP).

Panel A: Value-weighted variables								
						Autocorrelation		
	Obs	Mean	Std	Min	Max	1	2	3
σ(BM)	42	19.39	12.18	7.95	61.04	0.89	0.73	0.59
σ(DP)	42	31.65	23.91	10.69	99.87	0.92	0.82	0.71
σ(EP)	42	19.04	14.87	7.43	75.89	0.85	0.71	0.55
cd(BM)	42	0	5.84	−8.63	23.19	0.63	0.09	−0.25
cd(DP)	42	0	8.07	−28.66	31.24	0.49	0.17	−0.17
cd(EP)	42	0	7.06	−9.37	34.30	0.47	0.17	−0.16
CVD	42	0	1.00	−2.22	4.45	0.58	0.13	−0.21
Panel B: Equal-weighted variables								
						Autocorrelation		
	Obs	Mean	Std	Min	Max	1	2	3
σ(BM)	42	0.79	0.12	0.59	1.27	0.69	0.47	0.41
σ(DP)	42	1.00	0.17	0.63	1.29	0.89	0.76	0.63
σ(EP)	42	0.92	0.15	0.63	1.37	0.80	0.63	0.49
cd(BM)	42	0	0.10	−0.16	0.39	0.52	0.20	0.10
cd(DP)	42	0	0.08	−0.18	0.15	0.66	0.34	0.08
cd(EP)	42	0	0.08	−0.13	0.28	0.38	−0.04	−0.26
CVD	42	0	1.00	−2.07	3.59	0.44	0.00	−0.23

Table 2: Regression of the annual dispersion variables on a time index

This table reports the results by regressing the annual dispersion variables on a time index (and the squared time index) over the period 1963–2004. Each dependent variable is formed based on all available firms in NYSE, AMEX, and NASDAQ. The independent variable t-index is a time index taking values of 1, 2, 3... The independent variable t^2-index is the squared t-index. Dependent variables in Panel A are in a value-weighted scheme and those in Panel B are in an equal-weighted scheme. The variables σ(BM), σ(DP), and σ(EP) are, respectively, the cross-sectional standard deviation of logarithmic firm book-to-market equity, dividend-to-price ratios, and earnings-to-price ratio. OLS t-statistics are reported below the coefficients and the two-tailed p-values are reported in parenthesis. R-squares are adjusted for degree of freedom.

Panel A: Value-weighted			
	σ(BM)	σ(DP)	σ(EP)
Intercept	19.27	18.21	15.33
	6.62	*4.53*	*4.36*
	(0.00)	*(0.00)*	*(0.00)*
t-index	−1.33	−1.32	−1.24
	−4.25	*−3.07*	*−3.29*
	(0.00)	*(0.00)*	*(0.00)*
t^2-index	0.05	0.07	0.05
	6.79	*7.17*	*5.97*
	(0.00)	*(0.00)*	*(0.00)*
R^2	77%	88%	77%

Panel B: Equal-weighted			
	σ(BM)	σ(DP)	σ(EP)
Intercept	0.67	0.75	0.71
	21.76	*30.23*	*28.32*
	(0.00)	*(0.00)*	*(0.00)*
t-index	0.01	0.01	0.01
	4.49	*11.82*	*9.96*
	(0.00)	*(0.00)*	*(0.00)*
R^2	32%	77%	71%

Table 3: Correlation matrix

Panel A reports the Pearson correlations of cross-firm valuation dispersion (CVD) and its underlying measures. Panel B reports the correlations of the well-known aggregate predictors and the value- and equal-weighted CVDs. The value-weighted (equal-weighted) CVD is denoted as CVD_{vw} (CVD_{ew}) in Panel B. Aggregate dividend yield (D/P) is computed following Fama and French (1988a). Annual dividends are used. Past market return (Rm) is the past one-year CRSP value-weight index returns. Term premium (TERM) is defined as the difference between the 10-Year treasury constant maturity rate and the one-year treasury constant maturity rate. Default premium (DEF) is defined as the difference between the Moody's seasoned Aaa corporate bond yield and the Moody's seasoned Baa corporate bond yield. Short term interest rate (TBILL) is measured by the one-month treasury bill rate obtained from Ibbotson Associates. Aggregate relative equity issuance (S) is obtained from Wurgler's website over the period 1962–2002. The consumption-wealth ratio (*cay*) is obtained from Lettau's website from 1951 to 2003. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level based on the two-tailed p-value.

Panel A: Correlations of dispersion measures

	VW			EW		
	CVD	*cd*(BM)	*cd*(DP)	CVD	*cd*(BM)	*cd*(DP)
cd(BM)	0.97***			0.69***		
cd(DP)	0.94***	0.88***		0.78***	0.18	
cd(EP)	0.94***	0.88***	0.81***	0.94***	0.56***	0.68***

Panel B: Correlations of aggregate return predictors

	CVD_{vw}	CVD_{ew}	Rm	D/P	TERM	DEF	TBILL	S
CVD_{ew}	0.75**							
Rm	−0.02	0.11						
D/P	−0.32**	−0.10	−0.23					
TERM	−0.27*	−0.18	0.07	−0.23				
DEF	−0.03***	0.25	−0.18	0.54***	0.19			
TBILL	0.11	0.34**	−0.11	0.67***	−0.48***	0.57***		
S	0.08	0.23	−0.28*	0.59***	−0.31**	0.44***	0.55***	
cay	−0.72***	−0.41***	−0.05	0.32**	0.33**	0.00	0.14	−0.06

Table 4: CVD and aggregate indicators of heterogeneous beliefs and overconfidence

Panel A reports the regression results of the monthly aggregate trading volume and aggregate idiosyncratic volatility on the end-of-month cross-firm valuation dispersion (CVD). The monthly aggregate trading volume (TURN_a) is calculated as the weighted average of monthly turnover ratios of all available firms, in which turnover is the ratio of trading volume within the month over the end-of-month total shares outstanding and trading volume is divided by 2 for NASDAQ firms. The aggregate idiosyncratic return volatility (VOL_a) is the weighted average of firm daily idiosyncratic return volatilities within the month, in which idiosyncratic returns are calculated as the residuals from the Fama-French 3 factor model. Panel B reports the regression results of the changes in TURN_a and in VOL_a on the changes in CVD. ΔTURN_a, ΔTURN_a, and ΔCVD are, respectively, the difference between the value at month t and that at month $t-1$. In both Panels A and B, the value-weighted (equal-weighted) dependent variables are regressed on the value-weighted (equal-weighted) independent variables. Panel C reports the monthly regression results of the value- or equal-weighted end-of-month CVD on the past 24 or 36 value-weighted market returns. Panel D reports the monthly regression of the value- or equal-weighted ΔCVD on both past one-month value-weighted market returns and past 12 month value-weighted market returns. The OLS t-statistics are reported below the coefficients. In Panels A and B, the two-tailed OLS p-values are in parentheses. In Panels C and D, in parentheses are the two-tailed p-values from the simulated distribution using the method by Nelson and Kim (1993). R-squares are adjusted for degree of freedom.

Panel A: Regression $Y_t = \alpha + c\text{CVD}_t + \epsilon_t$				
	Value-weighted measures		Equal-weighted measures	
Y	TURN_a	VOL_a	TURN_a	VOL_a
c	0.042	0.253	0.047	0.228
	9.62	*24.76*	*5.67*	*9.29*
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
R^2	16%	55%	6%	15%
Panel B: Regression $\Delta Y_t = \alpha + c\Delta\text{CVD}_t + \epsilon_t$				
	Value-weighted measures		Equal-weighted measures	
ΔY	ΔTURN_a	ΔVOL_a	ΔTURN_a	ΔVOL_a
c	0.027	0.059	0.062	0.088
	1.63	*1.71*	*3.24*	*2.21*
	(0.10)	*(0.09)*	*(0.00)*	*(0.03)*
R^2	0%	0%	2%	1%
Panel C: Regression $\text{CVD}_t = \alpha + m\text{MKT}_{(t-\tau,t)} + \epsilon_t$				
	Value-weighted CVD		Equal-weighted CVD	
	$\text{MKT}_{(t-24,t)}$	$\text{MKT}_{(t-36,t)}$	$\text{MKT}_{(t-24,t)}$	$\text{MKT}_{(t-36,t)}$
m	0.446	0.791	0.779	1.104
	2.15	*4.49*	*3.80*	*6.42*
	(0.00)	*(0.00)*	*(0.00)*	*(0.00)*
R^2	1%	4%	3%	7%
Panel D: Regression $\Delta\text{CVD}_t = \alpha + m_1\text{MKT}_{(t-1,t)} + m_2\text{MKT}_{(t-12,t)} + \epsilon_t$				
	Value-weighted CVD		Equal-weighted CVD	
	$\text{MKT}_{(t-1,t)}$	$\text{MKT}_{(t-12,t)}$	$\text{MKT}_{(t-1,t)}$	$\text{MKT}_{(t-12,t)}$
m_1/m_2	0.288	0.271	0.852	0.209
	1.17	*3.89*	*2.62*	*2.27*
	(0.25)	*(0.00)*	*(0.01)*	*(0.03)*
R^2	3%		2%	

Table 5: Predictability of market excess returns

This table reports results by regressing market excess returns on the lagged cross-firm valuation dispersion (CVD). The CRSP value-weighted and equal-weighted indices are used as the value-weighted and equal-weighted market portfolios. Subsequent one-quarter, one-year, and three-year returns in excess of the risk-free rate are used as dependent variables. Panel A shows the results for the full sample in which CVD from 1963 to 2003 is used. Panel B shows the results for the subperiod in which CVD from 1963 to 1996 is used. The value-weighted (equal-weighted) CVD is used to predict the value-weighted (equal-weighted) returns. In forecasting one-quarter returns, the predictors are updated at the end of each March, June, September, and December. In forecasting one-year or three-year returns, they are updated annually at the end of each June. Overlapping observations are used for the three-year return regressions. The coefficients of OLS regressions are reported, below which in parentheses are the one-tail p-values of the coefficients in the simulated distribution using the method by Nelson and Kim (1993). R-squares are adjusted for degree of freedom.

Panel A: Full sample 1963-2003

	VW			EW		
	3-mon	1-yr	3-yr	3-mon	1-yr	3-yr
Intercept	1.22	4.74	13.68	2.17	7.96	22.97
	(0.00)	*(0.00)*	*(0.00)*	*(0.01)*	*(0.01)*	*(0.00)*
CVD	−2.38	−8.34	−18.97	−2.58	−8.76	−12.74
	(0.00)	*(0.00)*	*(0.00)*	*(0.01)*	*(0.01)*	*(0.00)*
R^2	6%	22%	51%	3%	12%	12%
Obs	163	41	40	163	41	40

Panel B: Subperiod 1963−1996

	VW			EW		
	3-mon	1-yr	3-yr	3-mon	1-yr	3-yr
Intercept	0.66	2.82	11.16	1.84	7.24	21.38
	(0.01)	*(0.02)*	*(0.00)*	*(0.03)*	*(0.03)*	*(0.01)*
CVD	−4.61	−16.60	−31.88	−2.40	−11.10	−17.45
	(0.01)	*(0.02)*	*(0.00)*	*(0.03)*	*(0.03)*	*(0.01)*
R^2	7%	22%	45%	2%	11%	14%
Obs	135	34	34	135	34	34

Table 6: Predictability of market excess returns with control variables

This table reports regression results of market excess returns on cross-firm valuation dispersion (CVD) with controls for a set of well-known predictors, including aggregate dividend yields (D/P), short term interest rates (TBILL), past market returns (Rm), term premium (TERM), default premium (DEF), aggregate relative equity issuances (S), and the consumption-wealth ratios. The CRSP value-weighted and equal-weighted indices are used as the value-weighted and equal-weighted market portfolios. Subsequent one-quarter, one-year, and three-year returns in excess of the risk-free rate are used as dependent variables. Panel A shows the results for the value-weighted market excess returns and Panel B shows the results for the equal-weighted market excess returns. The value-weighted (equal-weighted) CVD and Rm are used to predict the value-weighted (equal-weighted) returns. In forecasting one-quarter returns, the predictors are updated at the end of each March, June, September, and December. In forecasting one-year or three-year returns, they are updated annually at the end of each June. Overlapping observations are used for the three-year return regressions. The coefficients of OLS regressions are reported, below which in parentheses are the one-tail p-values of the coefficients in the simulated distribution using the method by Nelson and Kim (1993). R-squares are adjusted for degree of freedom.

Panel A: Forecasting value-weighted market excess returns

Intercept	CVD	Rm	D/P	TERM	DEF	TBILL	S	*cay*	R^2
One-quarter-ahead returns									
−2.64		0.00	1.92	0.45	1.43	−8.32			2%
(0.41)		*(0.49)*	*(0.02)*	*(0.31)*	*(0.24)*	*(0.06)*			
−0.33	−2.13	−0.02	0.69	−0.19	3.26	−7.68			6%
(0.39)	*(0.01)*	*(0.39)*	*(0.26)*	*(0.41)*	*(0.05)*	*(0.06)*			
−169.88		0.00	0.41	−1.82	5.30	−14.95		239.56	9%
(0.48)		*(0.49)*	*(0.36)*	*(0.04)*	*(0.00)*	*(0.00)*		*(0.00)*	
−153.93	−0.46	0.00	0.28	−1.75	5.34	−14.19		217.45	9%
(0.00)	*(0.32)*	*(0.47)*	*(0.43)*	*(0.04)*	*(0.00)*	*(0.00)*		*(0.00)*	
One-year-ahead returns									
−10.74		−0.10	6.63	5.76	−4.56	−4.60	−16.86		8%
(0.22)		*(0.27)*	*(0.18)*	*(0.06)*	*(0.33)*	*(0.37)*	*(0.35)*		
−3.33	−6.44	−0.11	2.54	3.10	1.42	−7.00	−0.37		16%
(0.25)	*(0.07)*	*(0.24)*	*(0.40)*	*(0.23)*	*(0.40)*	*(0.34)*	*(0.48)*		
−175.19		−0.08	5.18	3.06	2.19	−16.21	−10.84	234.02	7%
(0.44)		*(0.32)*	*(0.32)*	*(0.23)*	*(0.40)*	*(0.20)*	*(0.39)*	*(0.26)*	
195.11	−8.28	−0.14	3.11	5.57	−4.94	6.18	−2.85	−279.39	15%
(0.45)	*(0.02)*	*(0.19)*	*(0.48)*	*(0.07)*	*(0.33)*	*(0.39)*	*(0.48)*	*(0.17)*	
Three-year-ahead returns									
−19.00		−0.16	4.76	19.22	−40.04	70.89	45.12		24%
(0.39)		*(0.12)*	*(0.37)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.12)*		
4.89	−19.04	−0.16	−7.81	11.35	−18.27	56.88	89.88		60%
(0.36)	*(0.00)*	*(0.16)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.00)*	*(0.01)*		
−1309.28		0.09	−4.58	−3.28	22.10	−40.06	86.24	1827.34	59%
(0.00)		*(0.31)*	*(0.03)*	*(0.22)*	*(0.03)*	*(0.06)*	*(0.04)*	*(0.00)*	
−760.61	−11.91	−0.01	−8.58	1.10	10.02	−2.94	97.25	1071.46	66%
(0.00)	*(0.01)*	*(0.47)*	*(0.00)*	*(0.45)*	*(0.15)*	*(0.39)*	*(0.03)*	*(0.00)*	

Table 6: Predictability of market excess returns with control variables (cont'd)

Panel B: Forecasting equal-weighted market excess returns									
One-quarter-ahead returns									
Intercept	CVD	Rm	D/P	TERM	DEF	TBILL	S	*cay*	R^2
−1.14		−0.09	2.80	−0.45	6.12	−23.27			7%
(0.40)		*(0.14)*	*(0.01)*	*(0.37)*	*(0.01)*	*(0.00)*			
−0.78	−2.11	−0.09	1.49	−0.43	7.60	−18.38			8%
(0.42)	*(0.02)*	*(0.12)*	*(0.11)*	*(0.37)*	*(0.00)*	*(0.00)*			
−179.59		−0.08	1.21	−2.89	10.16	−30.12		255.48	10%
(0.49)		*(0.14)*	*(0.14)*	*(0.02)*	*(0.00)*	*(0.00)*		*(0.00)*	
−160.81	−0.94	−0.08	0.79	−2.62	10.42	−27.28		228.88	10%
(0.00)	*(0.17)*	*(0.06)*	*(0.21)*	*(0.01)*	*(0.00)*	*(0.00)*		*(0.00)*	
One-year-ahead returns									
−5.39		−0.26	12.49	4.87	0.76	−32.59	−70.10		20%
(0.27)		*(0.03)*	*(0.04)*	*(0.16)*	*(0.38)*	*(0.06)*	*(0.07)*		
−5.67	−3.87	−0.23	10.08	4.25	4.22	−27.72	−56.57		20%
(0.28)	*(0.19)*	*(0.05)*	*(0.18)*	*(0.22)*	*(0.29)*	*(0.14)*	*(0.17)*		
172.43		−0.27	14.13	7.77	−6.44	−20.37	−76.81	−253.17	19%
(0.47)		*(0.02)*	*(0.03)*	*(0.07)*	*(0.35)*	*(0.17)*	*(0.05)*	*(0.21)*	
276.00	−5.09	−0.25	11.91	8.65	−6.09	−6.84	−62.94	−401.15	20%
(0.49)	*(0.10)*	*(0.03)*	*(0.07)*	*(0.05)*	*(0.38)*	*(0.34)*	*(0.10)*	*(0.13)*	
Three-year-ahead returns									
11.27		−0.14	12.52	8.47	−23.64	−1.70	−43.34		−1%
(0.24)		*(0.21)*	*(0.03)*	*(0.08)*	*(0.07)*	*(0.49)*	*(0.25)*		
13.08	−9.59	−0.14	6.31	7.09	−13.59	8.10	−17.73		2%
(0.23)	*(0.06)*	*(0.21)*	*(0.19)*	*(0.12)*	*(0.21)*	*(0.40)*	*(0.38)*		
−429.33		−0.12	8.37	1.26	−4.84	−33.64	−29.55	628.32	−1%
(0.00)		*(0.07)*	*(0.14)*	*(0.38)*	*(0.33)*	*(0.06)*	*(0.24)*	*(0.03)*	
−260.19	−8.39	−0.13	4.52	2.79	−3.19	−12.91	−12.38	389.38	0%
(0.06)	*(0.07)*	*(0.13)*	*(0.41)*	*(0.31)*	*(0.47)*	*(0.27)*	*(0.39)*	*(0.18)*	

Table 7: Predictability of market excess returns with valuation spreads

This table reports results by regressing market excess returns on the lagged cross−firm valuation dispersion (CVD) and several valuation spreads during 1963-2004 in the following two regressions:

$$(1) \quad R_{t+1} = \alpha + \gamma_1 \mathrm{V}_t + \epsilon_{t+1},$$
$$(2) \quad R_{t+1} = \alpha + \gamma_2 \mathrm{V}_t + \eta \mathrm{CVD}_t + \epsilon_{t+1},$$

where V refers one of the following four measures of valuation spreads: the book-to-market spread (BMsp), the market-to-book spread (MBsp), the value spread (Vsp). and the small value (SVsp). BMsp (MBsp) is the difference of book-to-market (market-to-book) equity between value firms and growth firms. The value spread is defined as the difference in logarithmic book-to-market equity between value firms and growth firms. Value firms and growth firms in the first three spreads are the top and bottom book-to-market deciles. The small value spread is the value spread in small firms, obtained from Campbell & Vuolteenaho (2004). The value-weighted (equal-weighted) CVD is used to predict the value-weighted (equal-weighted) returns. Overlapping observations are used for the three-year return regressions. The coefficients of OLS regressions are reported, below which in parentheses are the one-tail p-values of the coefficients in the simulated distribution using the method by Nelson and Kim (1993). R-squares are adjusted for degree of freedom.

		Value-weighted				Equal-weighted			
Panel A: One-quarter-ahead returns									
Reg		BMsp	MBsp	Vsp	SVsp	BMsp	MBsp	Vsp	SVsp
(1)	γ_1	0.02	−1.23	−0.98	−1.33	2.03	−2.09	−0.80	−1.54
		(0.46)	*(0.06)*	*(0.16)*	*(0.06)*	*(0.04)*	*(0.03)*	*(0.28)*	*(0.09)*
	R^2	−1%	1%	1%	2%	2%	2%	0%	1%
(2)	γ_2	0.49	0.12	0.21	−0.32	2.47	−1.00	1.23	−0.39
		(0.30)	*(0.49)*	*(0.42)*	*(0.37)*	*(0.02)*	*(0.23)*	*(0.28)*	*(0.39)*
		CVD				CVD			
(2)	η	−2.46	−2.43	−2.47	−2.15	−2.90	−1.96	−3.29	−2.12
		(0.00)	*(0.01)*	*(0.01)*	*(0.02)*	*(0.01)*	*(0.06)*	*(0.02)*	*(0.05)*
	R^2	6%	6%	6%	6%	8%	5%	5%	2%
Panel B: One-year-ahead returns									
Reg		BMsp	MBsp	Vsp	SVsp	BMsp	MBsp	Vsp	SVsp
(1)	γ_1	−0.51	−3.65	−3.28	−6.10	6.53	−6.28	−3.21	−7.41
		(0.31)	*(0.15)*	*(0.17)*	*(0.00)*	*(0.08)*	*(0.07)*	*(0.24)*	*(0.04)*
	R^2	−2%	3%	2%	11%	6%	6%	0%	8%
(2)	γ_2	1.03	1.12	1.35	−2.49	6.89	−1.96	2.95	−3.91
		(0.44)	*(0.31)*	*(0.30)*	*(0.26)*	*(0.05)*	*(0.43)*	*(0.28)*	*(0.29)*
		CVD				CVD			
(2)	η	−8.54	−9.01	−9.11	−6.71	−9.05	−7.50	−10.66	−5.20
		(0.00)	*(0.01)*	*(0.01)*	*(0.03)*	*(0.00)*	*(0.04)*	*(0.02)*	*(0.18)*
	R^2	20%	20%	20%	20%	19%	10%	10%	8%
Panel C: Three-year-ahead returns									
Reg		BMsp	MBsp	Vsp	SVsp	BMsp	MBsp	Vsp	SVsp
(1)	γ_1	−0.91	−4.79	−3.22	−8.61	16.68	−9.49	−1.49	−7.69
		(0.37)	*(0.19)*	*(0.23)*	*(0.01)*	*(0.00)*	*(0.06)*	*(0.36)*	*(0.07)*
	R^2	−2%	−1%	2%	9%	25%	7%	−2%	3%
(2)	γ_2	2.59	7.78	9.58	2.31	17.21	−3.52	10.01	0.67
		(0.19)	*(0.00)*	*(0.00)*	*(0.21)*	*(0.00)*	*(0.28)*	*(0.05)*	*(0.46)*
		CVD				CVD			
(2)	η	−19.50	−23.83	−24.79	−20.30	−13.49	−10.37	−19.57	−12.45
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.00)*	*(0.04)*
	R^2	50%	56%	60%	50%	40%	10%	16%	8%

Table 8: Predictability of portfolio excess returns

This table reports the regression results of annual excess returns of beta (BETA) and volatility (VOL) quintiles on the lagged CVD, with and without controls for the return comovement with a set of well-known common factors, including market excess returns (MKT), the size factor (SMB), the book-to-market factor (HML), the momentum factor (UMD), the innovation in the instantaneous real interest rate ($\Delta\gamma$), and the instantaneous market Sharpe ratio ($\Delta\eta$), obtained from French's and Xia's websites. The long-short portfolios (H−L) are long on the highest BETA or VOL quintile and short on the lowest BETA or VOL quintile. The coefficients of OLS regressions are reported. The one-tail p-values based on simulated distribution using the method by Nelson and Kim (1993) are reported in parenthesis. R-squares are adjusted for degree of freedom.

	L	2	3	4	H	H−L	L	2	3	4	H	H−L
			BETA						VOL			
Panel A: $R_{i,t+1} = \alpha + \eta \text{CVD}_t + \epsilon_i$												
η	−1.60	−2.70	−3.71	−8.77	−15.17	−13.57	−2.47	−6.75	−9.29	−14.30	−20.08	−17.62
	(0.26)	*(0.16)*	*(0.12)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.17)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*
R^2	−1%	1%	2%	14%	22%	26%	0%	12%	18%	24%	34%	39%
Panel B: Controlling for the 3 factors: $R_t = \alpha + \eta \text{CVD}_{t-1} + \beta \text{MKT}_t + s\text{SMB}_t + h\text{HML}_t + u_t$												
η	2.34	2.30	3.08	−1.69	−1.69	−4.03	2.35	0.19	−1.06	−1.85	−7.09	−9.44
	(0.01)	*(0.01)*	*(0.00)*	*(0.06)*	*(0.20)*	*(0.06)*	*(0.00)*	*(0.39)*	*(0.17)*	*(0.17)*	*(0.00)*	*(0.00)*
R^2	86%	88%	88%	89%	86%	62%	94%	92%	91%	84%	82%	64%
Panel C: Controlling for the 4 factors: $R_t = \alpha + \eta \text{CVD}_{t-1} + \beta \text{MKT}_t + s\text{SMB}_t + h\text{HML}_t + m\text{UMD}_t + u_t$												
η	2.40	2.20	2.97	−1.97	−1.74	−4.14	2.34	0.17	−1.11	−1.76	−7.42	−9.76
	(0.01)	*(0.01)*	*(0.00)*	*(0.02)*	*(0.19)*	*(0.05)*	*(0.00)*	*(0.41)*	*(0.15)*	*(0.19)*	*(0.00)*	*(0.00)*
R^2	86%	88%	89%	92%	85%	62%	94%	92%	91%	84%	83%	65%
Panel D: Controlling for the ICAPM factors: $R_t = \alpha + \eta \text{CVD}_{t-1} + \beta \text{MKT}_t + b\Delta\gamma_t + e\Delta\eta_t + u_t$												
η	0.25	3.28	2.78	−1.48	−7.21	−10.99	0.51	−1.20	−0.08	−2.70	−6.03	−6.54
	(0.47)	*(0.00)*	*(0.01)*	*(0.14)*	*(0.00)*	*(0.00)*	*(0.30)*	*(0.10)*	*(0.50)*	*(0.19)*	*(0.05)*	*(0.06)*
R^2	82%	87%	90%	86%	78%	46%	88%	93%	86%	68%	63%	19%

Table 9: Two-way sorts

This table reports the average annual excess returns of the two-way sorts based on BETA/VOL and the equal-weighted cross-firm valuation dispersion (CVD). At the end of each June, stocks are first sorted into BETA or VOL quintiles and the quintile returns from July of year t to June of year $t+1$ are calculated. Then the quintiles are sorted based on whether CVD at the end of June of year t is above or below the sample mean (zero). CVD is positive for 1967–75, 1980–87, 1990–91, 1996, and 1999–2001. Return differentials refer to the quintile return differences between the low CVD states (when CVD<0) and the high CVD states (when CVD>0). The long-short portfolios (H−L) are long on the highest BETA or VOL quintile and short on the lowest BETA or VOL quintile. All returns are in percent.

	L	2	3	4	H	H−L
				BETA		
Average	5.20	5.20	5.13	4.54	4.30	−0.89
CVD<0	6.40	6.57	7.34	10.97	13.42	7.02
CVD>0	4.26	4.13	3.40	−0.49	−2.83	−7.09
Differential	2.14	2.44	3.94	11.47	16.25	14.11
				VOL		
Average	5.65	4.66	4.75	4.73	5.58	−0.07
CVD<0	7.21	8.22	11.32	14.57	19.53	12.33
CVD>0	4.43	1.87	−0.39	−2.98	−5.33	−9.77
Differential	2.77	6.34	11.71	17.55	24.87	22.09

Table 10: Predictability of market excess returns (1926–1962)

This table reports results by regressing market excess returns on the lagged cross-firm valuation dispersion (CVD), the detrended cross-sectional dispersion of book-to-market equity (cd(BM)), or the detrended cross-sectional dispersion of dividend-to-price ratios (cd(DP)) over the period of 1926–1962. The value-weighted cd(BM) (cd(DP)) is the residuals by regressing the value-weighted cross-sectional standard deviation of logarithmic BM (DP) on a time index (t-index) and the squared time index (t^2-index). The equal-weighted cd(BM) (cd(DP)) is the residuals by regressing the equal-weighted cross-sectional standard deviation of logarithmic BM (DP) from 1926–1962 on t-index. The dependent variables are the one-year ahead or three-year ahead market excess returns. The value-weighted (equal-weighted) predictor is used to forecast the value-weighted (equal-weighted) returns. Overlapping observations are used for the three-year return regressions. The coefficients of OLS regressions are reported, below which in parentheses are the one-tail p-values of the coefficients in the simulated distribution using the method by Nelson and Kim (1993). R-squares are adjusted for degree of freedom.

	VW		EW	
	1-yr	3-yr	1-yr	3-yr
Panel A: $R_{t+1} = \alpha + \eta \text{CVD}_t + \epsilon$				
Intercept	7.53	22.35	10.54	31.18
	(0.02)	*(0.00)*	*(0.33)*	*(0.34)*
CVD	−13.30	−29.78	−7.12	−6.02
	(0.02)	*(0.00)*	*(0.33)*	*(0.34)*
R^2	16%	39%	0%	−2%
Panel B: $R_{t+1} = \alpha + \eta_1 cd(\text{BM})_t + \epsilon$				
Intercept	7.53	22.35	10.54	31.18
	(0.06)	*(0.00)*	*(0.43)*	*(0.23)*
η_1	−10.34	−31.04	5.52	11.90
	(0.06)	*(0.00)*	*(0.44)*	*(0.23)*
R^2	9%	42%	−1%	2%
Panel C: $R_{t+1} = \alpha + \eta_2 cd(\text{DP})_t + \epsilon$				
Intercept	7.53	22.35	10.54	31.18
	(0.01)	*(0.00)*	*(0.01)*	*(0.02)*
η_2	−13.35	−22.00	−17.48	−22.01
	(0.01)	*(0.00)*	*(0.01)*	*(0.02)*
R^2	16%	20%	16%	12%

Table 11: Predictability of market excess returns with undetrended cross-firm valuation dispersion

This table reports results by regressing market excess returns on the undetrended lagged cross-firm valuation dispersion (CVD_{raw}) while controlling for a quadratic or a linear time trend. The value-weighted (equal-weighted) CVD_{raw} is the first principal component of the value-weighted (equal-weighted) σ(BM), σ(DP), and σ(EP), none of which is detrended. The variable t-index is a time index that takes the value from 1, 2, 3 and the variable t^2-index is the squared t-index. The dependent variables are the one-year ahead or three-year ahead market excess returns. The value-weighted (equal-weighted) predictor is used to predict the value-weighted (equal-weighted) returns. Overlapping observations are used for the three-year return regressions. The coefficients of OLS regressions are reported, below which are the OLS t-statistics and in parentheses are the p-values. The p-values of CVD_{raw} are calculated based on the simulated distribution using the method by Nelson and Kim (1993). R-squares are adjusted for degree of freedom.

Panel A: Forecasting one−year ahead market excess returns								
VW					EW			
Intercept	CVD_{raw}	t-index	t^2-index	R^2	Intercept	CVD_{raw}	t-index	R^2
−7.03	−24.01	−1.80	0.08	22%	−24.73	−19.34	1.52	12%
−0.96	*−3.72*	*−1.84*	*2.76*		*−1.87*	*−2.69*	*2.52*	
(0.02)	*(0.00)*	*(0.07)*	*(0.01)*		*(0.31)*	*(0.00)*	*(0.02)*	
Panel B: Forecasting three−year ahead market excess returns								
Intercept	CVD_{raw}	t-index	t^2-index	R^2	Intercept	CVD_{raw}	t-index	R^2
−21.38	−49.54	−2.61	0.15	54%	−20.52	−23.97	2.03	8%
−2.48	*−6.47*	*−2.19*	*4.03*		*−1.03*	*−2.24*	*2.19*	
(0.02)	*(0.00)*	*(0.04)*	*(0.00)*		*(0.31)*	*(0.00)*	*(0.03)*	

Figure 1: Time-series of firm valuation dispersion variables

This figure plots the time series of the annual dispersion variables over the period 1963–2003. The variables σ(BM), σ(DP), and σ(EP) are, respectively, the cross-sectional standard deviation of logarithmic firm book-to-market equity, dividend-to-price ratios, and earnings-to-price ratio. Each variable is formed based on all available firms in NYSE, AMEX, and NASDAQ at the end of each June. The value-weighted cd(BM), cd(DP), and cd(EP) are, respectively, the residuals by regressing σ(BM), σ(DP), and σ(EP) on a time index and the squared time index. The equal-weighted cd(BM), cd(DP), and cd(EP) are, respectively, the residuals by regressing σ(BM), σ(DP), and σ(EP) on a time index. The variable CVD is defined as the first principal component of cd(BM), cd(DP), and cd(EP). Value-weighted measures are plotted with dark blue lines (darker) while equal-weighted measures are plotted with purple red lines (lighter).

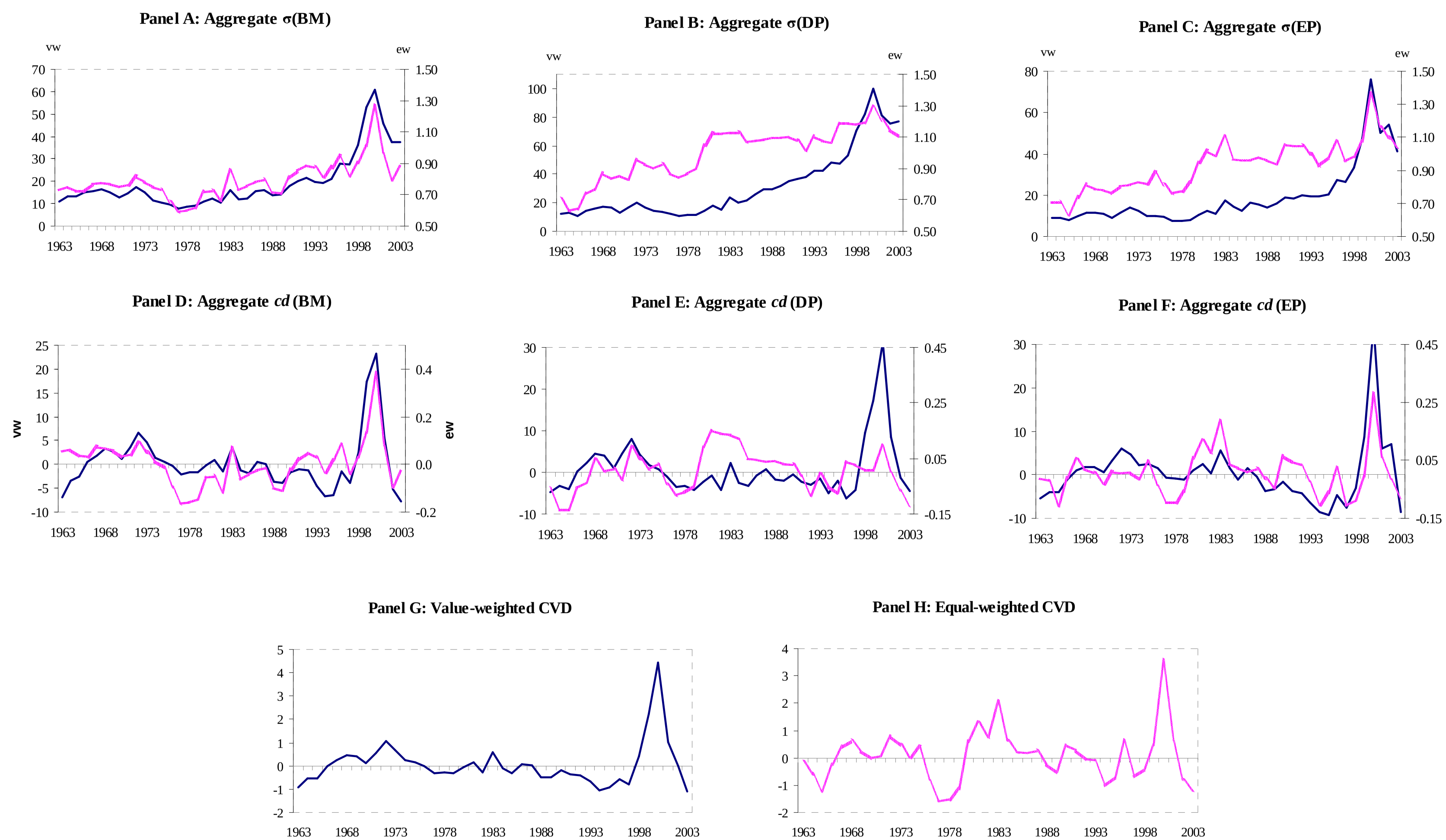

Figure 2: Time-series of dispersion in growth rates

This figure plots the time series of the annual dispersion variables of firm growth rates over the period 1963–2003. The variables $\sigma(\text{ROE})$, $\sigma(\Delta\text{D})$, and $\sigma(\Delta\text{E})$ are, respectively, the cross-sectional standard deviation of firm log return-on-equity, dividend growth, and earnings growth. Each variable is formed based on all available firms in NYSE, AMEX, and NASDAQ at the end of each June. Value-weighted measures are plotted with dark blue lines (darker) while equal-weighted measures are plotted with purple red lines (lighter).

Figure 3: Market excess returns sorted based on CVD

This figure plots subsequent three 12-month market excess returns sorted based on whether the end-of-June CVD is below (L) or above (H) its sample mean. The first 12-month returns are plotted in blue bar. The second 12-month returns are plotted in red bar. The third 12-month returns are plotted in ivory bar. Panels A and B are sorted based on the CVD from 1963–2003. Panels C and D are sorted based on the CVD from 1963–1996.