Beta × Forecast Dispersion*

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Abstract

We find that a positive (negative) CAPM security market line prevails for firms with low (high) dispersion in analysts' earnings forecasts. When heterogeneous investors disagree on cash flow growth under uncertainty, our theory states that a firm's stock price is an increasing function of the interaction between market beta and belief dispersion. Using forecast dispersion to proxy for the firm-level belief distribution, Fama-MacBeth (FMB) tests show that the interaction $\beta \times D$ significantly absorbs cross-sectional mispricing, producing an estimated price of market risk compatible with the observed equity premium. Our results provide insights into the beta anomaly and "tales" of the CAPM's conditional performance.

Keywords: Cross-Section of Returns, Beta Anomaly, Heterogeneous Beliefs, Disagreement and Uncertainty

JEL Codes: G12, G14

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1 Introduction

Empirical tests typically find a flatter security market line (SML) than predicted by conventional asset pricing models. This "beta anomaly" finding is consistent in both cross-sectional and time-series analyses (Fama and French (2004) discuss the classics[1] More recently Baker et al. (2011), Frazzini and Pedersen (2014), and Hong and Sraer (2016)). The puzzling beta anomaly motivates the search for additional risk factors, most prominently in Fama and French (1992), Hou et al. (2015), Fama and French (2016), and Stambaugh and Yuan (2017), to explain why some stocks earn high returns and others earn low returns. To the extent that proposed factors represent omitted variables from the true cross-sectional returns model, we should expect that including such factors in empirical tests will help resolve the beta anomaly. Thus far, this is not the case.

Recent literature has found that the beta anomaly is mitigated (or magnified) across mutually exclusive periods. Savor and Wilson (2014) document the predictive power of the market beta on macroeconomic announcement days. On trading days with scheduled FOMC announcements or labor market/inflation report statistical releases, the market earns high returns, and the single-factor CAPM predicts cross-sectional returns pretty well. On non-announcement days, the SML is flat or negative. Hendershott et al. (2020) extend the analysis to overnight vs. intraday returns: they find that market betas are positively (negatively) related to overnight (intraday) returns. Jylhä (2018), Chen et al. (2022) and Hasler and Martineau (2021) describe similar phenomena across periods of low (high) margin requirements, low (high) short selling efficiency, and high (low) expected returns, respectively. Savor and Wilson (2014) argue, however, that it is not possible to reconcile linear multi-factor models with these results since time-aggregation of returns implies such models should work consistently across mutually exclusive periods.

This paper documents that the beta anomaly is mitigated within stocks with a low degree

[1]Not limited to Friend and Blume (1970), Fama and MacBeth (1973), Gibbons et al. (1989), Stambaugh (1982), and Fama and French (1996).

of dispersion in analysts' EPS forecasts and magnified within stocks with a high degree. We provide a model in which when a firm exhibits high uncertainty regarding future cash flows, heterogeneous beliefs regarding cash flow risks results in overvaluation that is linear in the firm's market beta, even without short-sale constraints. This effect arises when the market clears based on reservation prices computed by heterogeneous investors, where reservation prices are a decreasing, convex function of uncertain discount rates[2]. Thus, low forecast dispersion firms have expected returns consistent with the CAPM and high dispersion firms have expected returns that deviate downward from the CAPM. Empirically, it turns out that this downward deviation is proportional to the firm's market beta interacted with the firm's forecast dispersion level.

To test our model, we transform analysts' forecast dispersion (D) into a cross-sectional firm-level measure and interact this measure with the firm's market beta (β). In Fama-MacBeth tests, the beta-forecast dispersion interaction ($\beta \times D$) absorbs the negative return component associated with overvaluation and allows the positive return component correlated with the market beta to price separately. Conditional on the $\beta \times D$ interaction, we estimate a price of market risk consistent with the observed equity premium, thus resolving the beta anomaly. Our finding is robust to controlling for commonly used anomaly factors or various measures of short-sale constraints, suggesting that our asset pricing model delivers reliable performance to account for both time-series and cross-sectional stylized facts.

Figure 1 illustrates our motivational finding. In Figure 1, we plot full-sample mean monthly (Panel A) and daily (Panel B) returns for test assets formed on stock-level market betas and forecast dispersion against asset-level full-sample CAPM market beta loadings[3]. Returns are value-weighted, and test assets are formed by simultaneously sorting stocks into lagged market beta deciles and lagged dispersion quintiles. Figure 1 depicts the results for the extreme dispersion quintiles (Q1 = Low Dispersion; Q5 = High Dispersion), with ten

[2]Related, Grinblatt and Linnainmaa (2011) show that relatively less risk-averse investors may prefer risky assets due to Jensen's inequality if key decision functions are concave or convex functions of unknown parameters.

[3]See Appendix A1 for a complete discussion of the construction of test assets.

beta-sorted test assets in each dispersion quintile.

[Insert Figure 1 About Here]

Focusing on the monthly returns depicted in Figure 1A, the SML for low dispersion test assets is positively sloped[4] (coefficient = 0.63%/mo.; t-Stat = 7.63) and the single-factor CAPM explains most variation in returns (R2 = 87.9%). High dispersion test assets realize no (or a weakly negative) market risk-return relation. The SML for high uncertainty test assets is not significantly downward-sloped (coefficient = -0.10%/mo.; t-Stat = -0.62) and the single-factor CAPM explains comparatively little variation in returns (R2 = 4.5%). The Q5-Q1 difference between slopes is significant and negative (coefficient = -0.73%/mo.; t-Stat = -3.95). Figure 1B depicts a similar pattern in daily returns.

The stylized facts exhibited in Figure 1 are robust in a wide range of cross-sectional anomalies. We repeat and document the analysis behind Figure 1 by forming 50 test assets on forecast dispersion within each of eight stock-level characteristics: market beta (as shown in Figure 1), alpha, idiosyncratic volatility (ivol), size, value, investment, profitability, and momentum. Stocks are simultaneously sorted based on lagged characteristics into characteristic decile and dispersion quintile test assets. In Table 1, we list the SMLs estimated within each dispersion quintile on the anomaly decile test assets in each quintile[5].

[Insert Table 1 About Here]

For low dispersion (Q1) test assets, the SML is positively sloped and significant (at the 10%-level or better) in seven of eight tested characteristics, and the Q5-Q1 difference between slopes is significant and negative in all eight. The SML point estimates decrease approximately linearly in dispersion quintiles almost uniformly across anomalies. Combining across

[4]See Table 1 for coefficient estimates and *t*-Stats.

[5]Each computed SML is the coefficient from the OLS regression of full-sample mean monthly excess returns on full-sample CAPM market beta loadings for 10 test assets in the dispersion quintile. Ivol and alpha are computed relative to the Fama and French (1992) plus momentum (Carhart (1997)) ("FFC") model

all anomalies, we find the SML for low dispersion test assets is positively sloped (coefficient = 0.71%/mo.; t-Stat = 8.55) and the SML for high dispersion test assets is negatively sloped (coefficient = -0.52%/mo.; t-Stat = -4.82). The former is roughly comparable to the mean excess market return in our sample period of 0.68%/mo. The Q5-Q1 difference between slopes is significant and negative (coefficient = -1.23%/mo.; t-Stat = -9.05). Hence, Figure 1 and Table 1 suggest that high dispersion stocks drive the beta anomaly; whereas, low dispersion stocks exhibit unconditional mean returns consistent with the CAPM[6].

In cross-sectional tests including our proposed $\beta \times D$ interaction, we estimate a market risk premium consistent with the observed market excess return and eliminate significant pricing errors. Our main Fama-MacBeth (1973) test (henceforth, "FMB") on *individual* stock returns benchmarked by the Fama and French (1992) plus momentum (Carhart (1997)) model (henceforth, "FFC") yields a highly significant and positive market risk price of 0.64%/mo. (t-Stat: 4.62) and an insignificant pricing error (as the FMB intercept). We compare this FMB price on estimated market betas to our in-sample mean market excess return of 0.68%/mo and find a p-value of 89.3% for the null hypothesis of equality. The $\beta \times D$ interaction carries a significant and negative price of -0.65%/mo. (t-Stat: -5.48)[7]. These findings are robust to controlling for the forecast dispersion anomaly (Diether et al. (2002)[8]), short sale constraints, benchmarking by alternative factor models, and previously cited measures of cross-sectional and time-series uncertainty or disagreement.

In our model, optimistic investors exhibit upwardly biased private estimates of the firm's value when firm-level uncertainty is high. Aggregating beliefs across investors results in prices for high dispersion stocks that deviate widely from fundamental values, though on average high dispersion stocks are overvalued. Informed investors, who have access to investment technology that filters noisy cash flows, develop private estimates for the firm's value closer

[6]In Appendix Figure 1, we recreate Figure 1 using the anomaly characteristic test assets used in Table 1

[7]When excluding $\beta \times D$, we estimate a market price of risk of 0.26%/mo. (t-Stat: 1.57). Conventionally, downward bias in the market beta SML is thought to arise from the omitted variable problem or measurement error. We view the inclusion of $\beta \times D$ as an omitted variable solution (Giglio and Xiu (2021)).

[8]The authors favor Miller's (1977) interpretation of overvaluation when pessimists are restricted by short-sale constraints.

to the firm's fundamental value and trade in the direction of fundamental value.

To verify this trading mechanism, we use the net arbitrage trading measure ("NAT") from Chen et al. (2019). NAT measures the net aggregate long and short trades from institutional arbitrageurs in a stock-quarter relative to the prior year. We find that arbitrageurs increase the magnitude of their trades (|NAT|) when $\beta \times D$ is high and tend to trade in the direction of future returns conditional on $\beta \times D$. We provide further evidence by examining the intraday vs. overnight return pattern documented by Hendershott et al. (2020). Recent theories and evidence attributes this pattern to heterogeneous trading between uninformed and informed investors (Lou et al. (2019), Lu et al. (2022)). We find nearly all the variation between the intraday and overnight SMLs is due to $\beta \times D$, suggesting that uninformed investors trade on inflated private valuations during the day and overpricing is corrected by informed investors towards the market close or overnight.

We use earnings announcements to test price reactions to the release of updated firm cash flow risk (Savor and Wilson (2016)). At the earnings announcement, all investors receive information relevant to revising firm-specific beliefs. This results in a relative shock to the private valuations of uninformed investors vs. informed investors. Testing FFC abnormal returns in a 10-day event window around earnings announcements, we find that the cumulative abnormal return correlated with $\beta \times D$ is significantly negative and the uncorrelated return is significantly positive. We interpret the uncorrelated return as ex-ante compensation for announcement risk and the correlated return as ex-post partial belief dispersion resolution. In our model, dispersion's directional relation to price is opposite that of risk: whereas downward revisions to a firm's risk increases the price of the firm's shares, downward revisions to the belief dispersion of a firm's investors decreases the price of the firm's shares. Optimists are forced into more "realistic" beliefs following earnings announcements, inducing a downward weighting of optimists' beliefs in the market price.

Finally, we examine pricing patterns related to the macroeconomic environment. We show our results are robust to the macro announcement effect of Savor and Wilson (2014), though there is little variation in the $\beta \times D$ FMB price on announcement and non-announcement days. This finding is consistent with macro announcement days revealing important systematic information but little relevant to investors' idiosyncratic firm-level beliefs. Importantly, including $\beta \times D$ recovers estimated market risk premiums consistent with the observed market return on both announcement days and non-announcement days. Thus, linear factor models including $\beta \times D$ aggregate over both types of days.

Related Literature: Our paper contributes to the empirical asset pricing literature by providing a parsimonious resolution of the beta anomaly and related asset pricing "tales." Our evidence supports the omitted variable interpretation of the failure of conventional factor models to price the equity market premium: our proposed $\beta \times D$ interaction absorbs the overpricing in high dispersion stocks and recovers theoretically predicted pricing patterns. These results show that uncertainty and investor heterogeneity are first-order effects in asset pricing and necessary considerations in future theoretical work. We do not focus on measurement error solutions to the beta anomaly; instead we provide a fundamental explanation of why market betas (on their own) fail to predict returns.

The $\beta \times D$ interaction does not add to the "zoo" (Cochrane (2011)) of proposed factors, many of which are challenged in replication tests (Hou et al. (2020)). Instead, we link the risk uninformed investors care about—the market beta (Berk and van Binsbergen (2016))—to the realized equity market premium. We successfully use the $\beta \times D$ interaction jointly with the prevailing multi-factor structures (i.e., Hou et al. (2015), Fama and French (2016), and Stambaugh and Yuan (2017)) to recover the market price of risk. In this sense, we are proposing a pricing model that aids in the recovery of theoretically implied risk prices and can remain agnostic towards the true underlying factor structure.

Alternative explanations for the beta anomaly focus on short sale constraints or investor preferences. For example, Black (1972) proposes a flat SML can result from borrowing constraints, an idea extended by Frazzini and Pedersen (2014) (Jylhä (2018) provides complementary results). A limitation of Black (1972), as pointed out by Hong and Sraer (2016), is that borrowing constraints are insufficient to explain negatively sloped SMLs. The latter are empirically observable, depending on the conditions: in the time-series for high beta stocks in Hong and Sraer (2016) or in the cross-section within high dispersion stocks in our paper. In this vein, our paper is more similar to behavioral explanations of the beta anomaly that focus on heterogeneous investors or alternative preferences (see lottery demand in Bali et al. (2017a)). Our paper contributes to this literature by providing an alternative mechanism to explain the beta anomaly: we propose overpricing linear in market betas arises when heterogeneous investors use a decreasing, convex function to compute their reservation prices on a security. Empirically, the analysts' EPS forecast dispersion for a firm proxies this overpricing when interacted with the firm's market beta allowing us to recover an estimate of the market risk premium consistent with the observed market return.

Finally, our results suggest careful consideration of the appropriate benchmark for abnormal return tests and evaluation of asset pricing models. We show that simple, ordinary least squares betas are "good enough" to predict returns in conventional econometric procedures when the $\beta \times D$ interaction is included. An open question is when including $\beta \times D$ in return benchmarks is appropriate. We re-estimate our earnings announcement results using modified characteristic-adjusted return benchmarks that control for $\beta \times D$ and find the same statistical significance but approximately half of the economic magnitude of our main result. Furthermore, understanding the extent to which our measure affects the performance of informed institutional investors and financial intermediation is an important area for future research.

2 Market Beta & Forecast Dispersion

Consider an economy with all equity firms. Suppose that firm i's cash flow process C_i follows

$$\frac{dC_i}{C_i} = \mu_i \cdot dt + \sigma_i \cdot dB_i \tag{1}$$

where dt is an infinitesimal time interval, μ_i is the constant fundamental cash flow growth rate, σ_i is the cash flow volatility, and B_i is a vector of Brownian motions reflecting the cash flow's sensitivity to independent market-wide (W) and idiosyncratic firm-level (Z_i) Brownian motions. We omit time t subscripts except when necessary for clarity. The firm-level Brownian shock can also be written as

$$\sigma_i \cdot dB_i = \beta_i \begin{bmatrix} 1 & \omega_i \end{bmatrix} \begin{bmatrix} dW \\ dZ_i \end{bmatrix} \tag{2}$$

where β_i is firm i's cash flow beta on the aggregate cash flow shock dW and ω_i is the ratio of the idiosyncratic risk sensitivity to the cash flow beta. Thus, $1/\omega_i$ is the signal-to-noise ratio β-averse investors in firm i face when valuing the firm's cash flows.

Suppose the idiosyncratic shock[9] is subject to disagreement between investors. Characterize investor j's belief ϕ_i^j relative to the signal-to-noise ratio[10] such that

$$dZ_i^j = dZ_i - \phi_i^j \cdot dt \tag{3}$$

where ϕ_i^j satisfies the Novikov condition. Using Girsanov's theorem, the cash flow process according to investor j's beliefs follows

$$\frac{dC_i^j}{C_i} = (\mu_i + \beta_i\phi_i^j)dt + \beta_i(dW + \omega_i \cdot dZ_i^j) \tag{4}$$

Define an optimistic investor as an investor with a positive belief $\phi_i^O > 0$. In Equation (4), the optimist anticipates strong firm performance reflected in their high perceived cash flow growth rate. The optimist's perceived cash flow growth rate exceeds the fundamental

[9]We could also introduce an uncertainty component to the systematic shock (W). Prior studies such as Chen and Epstein (2002) and Jeong et al. (2015) adopt this to model and study ambiguity aversion.

[10]The signal-to-noise ratio is similar to the speculative beta ratio proposed in Hong and Sraer (2016). The authors analyze disagreement over the market-wide shock, whereas we analyze disagreement in the idiosyncratic shock. The authors, nevertheless, find empirical evidence that the effect of idiosyncratic disagreement increases in the market beta. To be precise, the investor's beliefs ϕ_i^j is the component of idiosyncratic disagreement correlated with the market beta per unit of idiosyncratic risk.

growth rate proportional to the cash flow beta on the market shock (β_i) and the strength of their belief relative to the signal-to-noise ratio (ϕ_i^O). In contrast, define a pessimist as an investor with a negative belief $\phi_i^P < 0$ and, therefore, a perceived growth rate below the fundamental rate. Holding β_i constant, the optimist computes a high discounted value of the firm's cash flows (relative to fundamental value) and the pessimists computes a low value. Holding all else constant, increasing β_i increases the "wedge" between the optimist's and pessimist's computed discounted values by proportionally increasing the difference between the two investors' perceived growth rates.

To see this explicitly, we proceed by computing investor j's reservation price then finding the equilibrium price for firm i conditional on the belief dispersion across the investor population. Following Harrison and Kreps (1979), denote the stochastic discount factor as M and assume M depends only on market risk W such that

$$\frac{dM}{M} = -r \cdot dt - \lambda \cdot dW, \tag{5}$$

where r is the constant instantaneous risk-free rate and λ is the price of market risk[11]. Define asset i as the equity claim on firm i's cash flows with price P_i. Let $\mathcal{P}_i(\phi_i^j)$ denote the perceived value of asset i by investor j. At time t, the discounted cash flow value of firm i is computed by investor j according to

$$M_t \mathcal{P}_{i,t}(\phi_i^j) = E_t^j \left[\int_{s=t}^{\infty} M_s C_{i,s} \cdot ds \right] \tag{6}$$

Then, the following result holds.

Theorem 1 *For each asset i conditional on belief ϕ, solving for Equation (6) yields*

$$\mathcal{P}_{i,t}(\phi) = \frac{C_{i,t}}{r + \beta_i(\lambda - \phi) - \mu_i} \tag{7}$$

[11]We assume that idiosyncratic firm-level shocks net out in aggregate, such that aggregate cash flow depends only on the market-wide shock.

Proof. Equation (6) can be rewritten as

$$\mathcal{P}_{i,t}(\phi) = C_{i,t} \int_{s=t}^{\infty} e^{-(r+\beta_i(\lambda-\phi)-\mu_i)(s-t)} \cdot ds \tag{8}$$

We evaluate the integral to obtain the result. ■

Theorem 1 provides the reservation price for investor j with belief ϕ_i^j. Suppose that heterogeneous beliefs in the population are such that we can characterize investors according to a continuous uniform distribution $\phi_i \sim U[-\Phi_i, \Phi_i]$ with $\Phi_i > 0$. Assume that each individual's belief is private but the distribution of beliefs across the population is known publicly[12]. In an equilibrium, investors compare their reservation prices $(\mathcal{P}_i(\phi_i^j))$ to the equilibrium price P_i to determine their trading strategies. The optimistic investor's belief is such that $\mathcal{P}_i(\phi_i^O) > P_i$ and the pessimistic investor's belief is such that $\mathcal{P}_i(\phi_i^O) < P_i$. Based on this observation and tractability, we apply a linear demand rule $\theta(\phi_i^j)$ for asset i as follows

$$\theta(\phi_i) = \gamma(\mathcal{P}_i(\phi_i) - P_i) \tag{9}$$

where $\gamma > 0$ measures the degree of risk capacity. Note, we do not impose a short-sale constraint. Finally, normalize the total supply of asset i to 1. Then, the market clearing condition is

$$\int_{-\Phi_i}^{\Phi_i} \theta(\phi) \frac{d\phi}{2\Phi_i} = 1 \tag{10}$$

Under these conditions, the following theorem solves for the equilibrium price.

Theorem 2 *In equilibrium, the price of asset i is*

$$P_i = \int_{-\Phi_i}^{\Phi_i} \mathcal{P}_i(\phi) \frac{d\phi}{2\Phi_i} - \frac{1}{\gamma} \cong \frac{C_i}{r + \beta_i(\lambda - \Phi_i) - \mu_i} - \frac{1}{\gamma} \tag{11}$$

[12]In practice, consider that sell-side equity analysts will reveal their beliefs by publishing EPS estimates. Since the sell-side analysts estimates are publicly known, the distribution of investors' beliefs is publicly known (to the extent the former is a valid proxy for the latter).

Proof. Equations (9) and (10) imply that

$$P_i = \int_{-\Phi_i}^{\Phi_i} \mathcal{P}_i(\phi) \frac{d\phi}{2\Phi_i} - \frac{1}{\gamma} \tag{12}$$

Then, plugging Equation (7) into Equation (12) yields

$$\begin{aligned} P_i &= \int_{-\Phi_i}^{\Phi_i} \frac{C_i}{r + \beta_i(\lambda - \phi) - \mu_i} \frac{d\phi}{2\Phi_i} \\ &= \frac{C_i}{2\beta_i\Phi_i} \log\left(\frac{r + \beta_i(\lambda + \Phi_i) - \mu_i}{r + \beta_i(\lambda - \Phi_i) - \mu_i}\right) - \frac{1}{\gamma} \\ &\cong -\frac{C_i}{2\beta_i\Phi_i} \left(\frac{d}{d\Phi_i} \log\left(r + \beta_i(\lambda - \Phi_i) - \mu_i\right)\right) - \frac{1}{\gamma} \\ &= \frac{C_i}{r + \beta_i(\lambda - \Phi_i) - \mu_i} - \frac{1}{\gamma} \end{aligned} \tag{13}$$

where we apply the central difference approximation by perturbing Φ_i to derive the equilibrium price[13]. ■

Theorem 2 shows how the market value of firm i increases relative to fundamental value when the interaction between market risk and belief dispersion ($\beta_i \times \Phi_i$) is high, all else equal. The equilibrium price increases in Φ_i because the price is an increasing, convex function of the belief dispersion Φ_i[14]. We assume optimists and pessimists can fully participate in the market, though the results of Theorem 2 become stronger if short-sale constraints prevented the most pessimistic investors from participating. Note, the belief level at the margin (marginal investor) is determined by equalizing Equation (7) to Equation (11). If individual risk capacity is high ($\gamma \to \infty$), the most optimistic investor with $\phi_i^O = \Phi_i$ becomes the marginal investor. However, for sufficiently small γ the marginal investor exhibits $\phi_i^j <$

[13]The numerical differentiation recipe used in deriving Equation (13) is frequently used in computing a duration measure for bonds and solving partial differential equations. The method is highly accurate due to the utilization of two points to draw a parallel line to the true slope. The truncation error is the order of $O(h^2)$ with the step size h.

[14]We assume $0 < \Phi_i < \frac{r+\beta_i\lambda-\mu}{\beta_i}$.

Φ_i.

The asset pricing formula defined in Equation (11) turns out to be a belief dispersion augmented Gordon growth model. Therefore, we may define the expected excess rate of return up to the risk capacity γ as

$$E(r_i^e) \equiv \beta_i(\lambda - \Phi_i) \tag{14}$$

Cross-Section of Returns: Equation (14) provides a parsimonious model to test the cross-section of returns. If Φ_i is small, expected returns are proportional to market risk β_i. Hence, the stock returns of low Φ_i firms follow conventional factor models like the CAPM. If Φ_i is large, expected returns deviate downward proportional to $\beta_i \times \Phi_i$. To test these predictions, we can transform Equation (14) into the FMB cross-sectional regression

$$r_i^e = \lambda_0 + \lambda^{MKT} \cdot \beta_i + \lambda^{\beta \times D} \cdot (\beta \times D)_i + \varepsilon_i \tag{15}$$

where D_i is a normalized measure of dispersion in sell-side analysts' EPS forecasts and $\lambda^{\beta \times D}$ is the FMB price of the $\beta \times D$ interaction ("beta $\times$ forecast dispersion"). The identifying assumption is that the distribution of revealed sell-side analysts' beliefs (D_i) is publicly observable and proxies for the underlying distribution of investors' beliefs (Φ_i). If we measure β_i's with respect to the market portfolio, then Equation (14) implies that:

(A) $\lambda^{mkt} = r^{MKT}$

(B) $\lambda^{\beta \times D} < 0$

(C) $\lambda^0 = 0$

We interpret these relations that, conditional on including the $\beta \times D$ interaction: (A) consistent with β-averse investors demanding proportional to market returns to hold market risk, the FMB price of market risk (λ^{MKT}) equals the observed market excess return (r^{MKT});

(B) consistent with optimists' share of the market price increasing in β, the $\beta \times D$ interaction is correlated with overpricing in β; and (C) consistent with a complete cross-sectional pricing model, the FMB intercept is insignificant.

Optimists vs. Pessimists: In Equation (11), beliefs are uniformly distributed in the population. If the belief distribution shifts towards optimism or pessimism, the equilibrium price with shift towards overvaluation of undervaluation, respectively[15]. Proposition 1 formalizes this intuition.

Proposition 1 *Define the share of optimists in the population as $\Gamma_i \in (0,1)$ and the share of pessimists as $1 - \Gamma_i$. Assume optimists' (pessimists') beliefs are uniformly distributed between $[0, \Phi_i]$ $([-\Phi_i, 0))$. Then, the equilibrium price is*

$$\begin{aligned} P_i^* &= (1-\Gamma_i) \int_{-\Phi_i}^{0} \mathcal{P}_i(\phi) \frac{d\phi}{\Phi_i} + \Gamma_i \int_{0}^{\Phi_i} \mathcal{P}_i(\phi) \frac{d\phi}{\Phi_i} - \frac{1}{\gamma} \\ &= 2(1-\Gamma_i) \left(\int_{-\Phi_i}^{\Phi_i} \mathcal{P}_i(\phi) \frac{d\phi}{2\Phi_i} \right) + 2(\Gamma_i - 1/2) \left(\int_{0}^{\Phi_i} \mathcal{P}_i(\phi) \frac{d\phi}{\Phi_i} \right) - \frac{1}{\gamma} \\ &= 2(1-\Gamma_i) P_i + 2(\Gamma_i - 1/2) P_i^O \\ &= P_i + 2(\Gamma_i - 1/2)(P_i^O - P_i) \end{aligned} \quad (16)$$

where P_i is the equilibrium price computed in the base case of Equation (11) and P_i^O is the belief-weighted reservation price for optimists.

Following Proposition 1, we can write the difference between the equilibrium price under

[15]Related, Duffie et al. (2002) incorporate a security lending fee in model with heterogeneous beliefs to show that the extra cash flows available to long investors lead to higher asset prices than otherwise. The existence of lending fee imposes a short-sales constraint, reducing the price impact of short sellers. This feedback effectively increases the income streams of long positions to strengthen the overvaluation channel of the model.

belief shifting (P_i^*) and the uniform belief dispersion base case (P_i) as

$$P_i^* - P_i = 2(\Gamma_i - 1/2)(P_i^O - P_i) \tag{17}$$

As idiosyncratic sentiment varies, the equilibrium price increases when optimists outnumber pessimists ($\Gamma_i > 1/2$), and vice versa. Thus, we can infer that the trading strategy of informed investors (characterized by $\phi_i^j \to 0$) will depend on belief shifting. When optimists and pessimists are equally split in the population, the asset price is overvalued (due to the convexity of P_i) and informed investors compute reservation prices below the market price. When excessive pessimism (optimism) prevails, the asset price can drift below (far above) fundamental value. Thus, the trading direction of informed investors is likely to be long (short) when the population belief distribution drifts excessively pessimistic (optimistic).

Belief Updating: Finally, consider shocks to the firm-level information environment. While we do not explicitly model time variation in Φ_i, it is straightforward to describe the implications of shocks to these quantities from Equation (14). Downward shocks in Φ_i result in upward shocks to expected returns and downward shocks in price. The price reaction is magnified proportional to β_i.

3 Data & Methodology

We source data on analysts' estimates from the Institutional Broker's Estimate System (IBES) maintained by Thomson Reuters, stock market data from CRSP, and firm financials from COMPUSTAT. IBES contains financial projections and recommendations from sell-side equity analysts dating back to 1976. We base the dispersion measure (Barron et al. (1998)) on quarterly EPS estimates, which are widely available in IBES starting in 1984[16]. We track EPS estimates based on the revision date provided by IBES and exclude all estimates

[16] Quarterly EPS estimates are available for our sample from Feb.-1984. To achieve a minimum number of observations in first stage regressions for our Fama-MacBeth tests, our second stage cross-sectional regressions use data starting from Aug.-1986.

posted following the firm's earnings reporting date or that have not been updated within 105 trailing days[17]. We require a minimum of two valid outstanding analyst estimates in order to calculate dispersion. We include common stocks from CRSP (share codes 10 and 11) for which we can match valid forecast data.

In Table 2, we compare our sample to the CRSP universe. Panel A lists summary statistics at the beginning of our sample (02/1984), at five-year increments within our sample, and at the end of our sample (12/2022). On average, our sample includes larger firm-months than the CRSP universe and the sample share of CRSP increases in the second-half of our sample period. The sample share of CRSP maximizes in 2015, when our sample captures 73.1% of the CRSP universe. Panel B compares the CRSP universe to our sample and firm-months outside of our sample. Figures listed are monthly means. The mean monthly count of firms in our sample is 2,286 (vs. 5,193 in CRSP) and the mean size (as the market-value of equity, in $MM) is 5,148.8 (vs. 3,167.3 in CRSP). CRSP firm-months outside of our sample are small (the mean size is 268.8), which skews the comparison of the CRSP universe to our sample. Panel C compares our sample firms across the months these firms appear in our sample with the months these firms appear in CRSP but not in our sample. For our sample firms, we capture 61.0% of all months the firm appears in CRSP (on average, sample firms appear 151.8 months in CRSP and 92.6 months in our sample). Typically, sample firms are smaller when appearing in CRSP but not in our sample. To the extent that we attribute our main effects to the firm's information environment, testing the IBES universe biases against our interpretation: our sample firms are larger and generally covered by at least a half-dozen sell-side analysts. In robustness tests, we show our results do not vary by sample sub-period, firm size, or analyst coverage.

[Insert Table 2 About Here]

Computing Firm-Level Dispersion: We use dispersion in analysts' estimates to con-

[17]IBES excludes estimates older than 105 days from the consensus estimate calculation recorded in the database.

struct our cross-sectional measure (Barron et al. (1998)). At each earnings announcement date, we collect the valid outstanding quarterly EPS estimates posted prior to the announcement in IBES and the actual EPS announced for the quarter. Dispersion is defined as the variance in forecasts scaled by the absolute value of the actual. After calculating dispersion, we lag dispersion into the next month after the earnings announcement and keep the observed value in our sample until the next lagged measure is available or until six months have passed. Thus, for firm i in month t, dispersion is given by

$$Dispersion_{i,t} = var(Forecast_{j,i,q})/abs(Actual_{i,q}) \tag{18}$$

where analyst j provides a valid forecast for the quarterly earnings announced in month $q < t$. Within each month, we rank dispersion cross-sectionally and normalize ranks between [0,1] to arrive at our cross-sectional measure. In this way, dispersion is transformed to a 0 to 1 proxy for $\omega_i \Delta_{\phi,i}$, as follows:

$$D_{i,t} = RANK_t^{\%}(Dispersion_{i,t}) \in [0, 1] \tag{19}$$

Two-Stage Regression Procedure: For each stock in our sample, we estimate rolling-window factor loadings based on monthly returns for the prior five years[18]. Our main benchmark for this first-stage regression is the FFC model. We compute the $\beta \times D$ interaction by multiplying the market beta estimated from the first-stage regression, $\hat{\beta}_{i,t}^{MKT}$, with the normalized dispersion measure, $D_{i,t}$, then demean cross-sectionally by the market value-weighted interaction in each month. For example, using the FFC model to benchmark returns in the first-stage, we estimate a rolling-window regression for each stock of the form:

[18]Our main tests use 60 monthly observations with a minimum of 30 monthly returns observed for inclusion. We test 24 month and 36 month rolling windows for robustness and find consistent results. For tests of daily returns, we estimate factor loadings for the prior 252 trading days (with a minimum of 126 returns observed for inclusion). In untabulated tests, we find our monthly results are consistent when using factor loadings estimated using the prior 252 trading days to predict monthly returns.

$$r_{i,t}^e = \alpha_i + \beta_i^{MKT} r_t^{MKTRF} + \beta_i^{SMB} r_t^{SMB} + \beta_i^{HML} r_t^{HML} + \beta_i^{UMD} r_t^{UMD} + \varepsilon_{i,t}^{(1)} \tag{20}$$

where $r_{i,t}^e$ is the excess return of stock i in month t. The $\beta \times D$ interaction factor for firm i in month t is then defined as:

$$\beta_{i,t} \times D_{i,t} \equiv \hat{\beta}_{i,t}^{MKT} \times D_{i,t} - \sum_{k=1}^{N} w_{k,t} D_{k,t} \hat{\beta}_{k,t}^{MKT} \tag{21}$$

where $w_{k,t}$ is the market capitalization of stock k divided by the total capitalization of all stocks included in the sample in month t using beginning of month market equity values.

Finally, we recover factor price estimates by lagging estimated factor loadings and using a second-stage Fama-MacBeth regression of the form:

$$r_{i,t}^e = \lambda_t^0 + \lambda_t^{MKT} \hat{\beta}_{i,t-1}^{MKT} + \lambda_t^{SMB} \hat{\beta}_{i,t-1}^{SMB} + \lambda_t^{HML} \hat{\beta}_{i,t-1}^{HML} + \lambda_t^{UMD} \hat{\beta}_{i,t-1}^{UMD} + \lambda_t^{\beta * D} \beta_{i,t-1} \times D_{i,t-1} + \varepsilon_{i,t-1}^{(2)} \tag{22}$$

We lag factor loadings into the next period prior to estimating each month's cross-sectional regression, thus we recover Fama-MacBeth prices relative to public information available at the beginning of each month. Coefficients reflect the average ex-ante compensation demanded by investors on each risk factor. Our primary tests use individual stock returns (Ang et al. (2019)) and we report results using test assets in the appendices.

In additional to the $\beta \times D$ interaction, we compute the standard deviation of normalized dispersion proxy $D_{i,t}$ as $\sigma(D_{i,t})$ in each rolling window. The volatility of dispersion proxies for a second-order effect of the $\beta \times D$ interaction: upward revisions in dispersion can result in an upward shift in the distribution of uninformed value estimates, increasing the equilibrium price. Hence, the volatility of dispersion is a risk informed investors face when going short overvalued stocks. Alternatively, the volatility of dispersion may represent a risk to the quality of informed investors' private information that decreases the effectiveness of their directional trading.

Additional Data: We collect factor returns for the FFC and Fama-French five-factors ("FF5") (Fama and French (2016)) models from Kenneth French's website. We collect factor returns for the q-factors ("QF") (Hou et al. (2015)) model from Lu Zhang's website and factor returns for the traded liquidity factor (Pástor and Stambaugh (2003)) and the mispricing factors ("MISP") (Stambaugh and Yuan (2017)) from Robert Stambaugh's website. We collect factor returns for the betting-against-beta ("BAB") (Frazzini and Pedersen (2014)) and lottery returns ("MAX") factors from Andrea Frazzini's and Turan Bali's websites, respectively. VIX data is based on the S&P 500 VIX Index from the CBOE. The economic uncertainty index from Jurado et al. (2015) index aggregates prediction errors from time-series regressions on relevant macroeconomic and macro-financial variables to proxy for the level of time-series uncertainty in the economy. Using this data, Bali et al. (2017b) find economic uncertainty is priced in the cross-section of returns. We download the economic uncertainty index from Sydney Ludvigson's website.

We capture informed trading using the net arbitrage trading ("NAT") measure from Chen et al. (2019). NAT measures the difference in hedge fund long positions and short-interest at a stock level, where both long and short data is de-trended over the trailing four quarters. We download the data from Yong Chen's website and lag the quarterly measure into the next quarter so that we test the prediction implied by arbitrageurs' past directional trading in future returns.

We collect macroeconomic announcement dates from the Bureau of Labor Statistics (BLS) and the Board of Governors of the Federal Reserve System websites (as in Savor and Wilson (2014)). From the BLS, we find inflation (producer price index, PPI) and labor report releases; from the Fed, we find scheduled FOMC meetings. We use PPI reports for inflation because the PPI release typically occurs before other inflation statistical releases. We use the last date of multiday FOMC meetings to proxy for interest rate announcements.

4 Main Results

This section presents our main empirical results. First, we document FMB tests of individual stock returns on lagged factor loadings including and excluding the $\beta \times D$ interaction. We show the inclusion of $\beta \times D$ recovers an estimate of the market price of risk consistent with the observed equity premium and eliminates pricing errors. Consistent with our asset pricing model, we show the $\beta \times D$ return relation is linear in the cross-section of returns and find significantly effects from both first- and second-order dispersion measures. Our main finding is robust in common factor structures and unrelated to alternative proxies for uncertainty or disagreement.

Fama-MacBeth Tests: Table 3 compares Fama-MacBeth results for individual stocks excluding and including the $\beta \times D$ interaction factor. Columns (1)-(4) list results for variations to the CAPM and (5)-(8) list results for variations to the FFC model. In both cases, we present results for the baseline model, the model controlling for the dispersion anomaly (Disagreement-Minus-Agreement, "DMA")[19], and the model including the $\beta \times D$ interaction factor. Coefficients listed in the table are monthly risk prices (in percentage points) estimated by the Fama-MacBeth procedure. t-Stats are listed below coefficients (in parentheses) computed using Newey-West standard errors with six-months of lags. $|t\text{-Stats}| > 2.00$ are indicated in **bold**.

Table 3 shows that when including the $\beta \times D$ interaction, the FMB price of market risk is highly significant and consistent with the in-sample equity premium. Across models, we estimate a price of market risk (MKT) between 0.61%/mo. and 0.64%/mo. with t-Stats between 3.92 and 4.62. This compares to an in-sample observed equity premium of 0.68%/mo. Excluding $\beta \times D$, we fail to estimate a significant price of market risk, consistent with the well-known beta anomaly. To provide further intuition for this result, we compute

[19]This is the factor loading estimated when including the long-short portfolio of low dispersion vs. high dispersion stocks studied in Diether et al. (2002). See Appendix A1 for a description of the construction of the DMA factor

p-values for the hypothesis test that our estimated price of market risk equals the observed equity premium[20]. Including $\beta \times D$, p-values range from 80.2% to 89.3%; whereas, excluding $\beta \times D$ we marginally reject the estimated risk price equals the observed risk price.

[Insert Table 3 About Here]

Including $\beta \times D$, furthermore, eliminates significant pricing errors. Taking FMB intercepts as pricing errors, we find that excluding $\beta \times D$ yields positive, significant errors and including $\beta \times D$ yields insignificant errors. The best performing specification includes the FFC factors and $\beta \times D$: in column (6), the pricing error is 0.18%/mo. with a t-Stat of 0.88. Together, these results are consistent with the inclusion of $\beta \times D$ resolving the omitted variable problem in FMB regressions. Examining $\beta \times D$, we see the interaction is highly significant and negatively priced. The point estimates for the FMB price on the $\beta \times D$ interaction range from -0.62%/mo. to -0.65%/mo. and the corresponding t-Stats range from -4.83 to -5.94. Thus, Fama-MacBeth testing is consistent with overvaluation in high dispersion stocks that is linear in market betas[21].

Linearity of $\beta \times D$ Effect: A potential concern in these FMB results is that a small subset of stocks are driving our findings. To address this concern, we examine the linearity of the $\beta \times D$ interaction. Following the methodology of Stambaugh et al. (2015), we estimate the relation between FFC abnormal returns and $\beta \times D$. For each month t, we compute individual stock FFC abnormal returns based on lagged factor loadings. Using the same lagged factor loadings, we compute the individual stock $\beta \times D$ then split stocks into deciles based on this measure. Once each stock i is assigned to a decile bucket $(\beta \times D)_d$, we estimate

$$\hat{e}_{i,t}^{FFC} = \omega_{0,t} + f_t(\beta_{i,t-1} \times D_{i,t-1}) + \eta_{i,t} \tag{23}$$

[20]For the 437 months tested in Table 3, the mean market excess return is 0.68%/mo. with a standard error of 0.22%/mo.

[21]We replicate these results in a pooled specification in Appendix Table 1. Using standard errors clustered by month and rolling, lagged factor loadings, we find all results are economically and statistically consistent across Fama-MacBeth and pooled specifications.

where $\hat{e}_{i,t}^{FFC}$ is the FFC abnormal return for stock i in month t. $f_t(\cdot)$ is a piecewise linear function with dummy variables for intercepts and interactions with $\beta \times D$ for each decile bucket, as follows:

$$f_t(\beta \times D) = \sum_{d=1}^{10} I(\beta \times D \in (\beta \times D)_d) \times (a_{d,t} + b_{d,t} \cdot \beta \times D) \tag{24}$$

To estimate Equation (23), we restrict coefficients $a_{d,t}$ and $b_{d,t}$ so that the function is continuous at decile threshold values and use the FMB procedure to find the mean value of the distribution function across our sample period.

We plot the results in Figure 2, where the x-axis is the percentile distribution of $\beta \times D$ in the population and the y-axis is mean monthly FFC abnormal returns (in bps).

[Insert Figure 2 About Here]

In Figure 2, the effect of $\beta \times D$ is linear and decreasing across the population distribution ($\beta \times D$ percentile). Average mispricing (relative to FFC) is low for low $\beta \times D$ stocks, and vice versa for high $\beta \times D$ stocks. The effect is not concentrated in any subset of the population. Instead, Figure 2 shows overvaluation increases linearly in the $\beta \times D$ nexus. We argue this validates our model's base case of uniformly distributed beliefs and proportional belief dispersion sensitivity. The statistical significance of the FMB price of $\beta \times D$, indeed, is driven by stocks in the inner quintiles of the normalized dispersion measure. In essence, risk-return relations follow proportionally shallower SMLs as dispersion increases.

Additional Forecast Dispersion Proxies: In Table 4, we present results benchmarked by the FFC that include higher-order risk and dispersion proxy variables. We test the dispersion level uncorrelated with the beta-dispersion interaction ($D_{i,t}$), the volatility of each firm's dispersion measure in the first-stage rolling window ($\sigma(D_{i,t})$), and higher-order interactions. We find our main results are unaffected by the inclusion of these variables in the second-stage, though the results of Diether et al. (2002) are recovered through including the state variable

$(D_{i,t})$[22]. FMB prices for the dispersion level range from -0.76%/mo. to -2.22%/mo. with t-Stats between -3.12 and -3.63. The volatility of dispersion is significantly and positively priced, and the effect is concentrated in high dispersion stocks (unconditionally in column (3), the volatility of dispersion carries a coefficient of 1.94%/mo. with a t-Stat of 3.69; interacted with dispersion in column (5), the coefficient is 6.90%/mo. with a t-Stat of 2.41.). Hence, the component of dispersion orthogonal to beta continues to have an important role in cross-sectional return patterns outside of our main findings. Also, the positive FMB price on the volatility of dispersion is consistent with our intuition that informed traders alternatively demand compensation for the risk to shorting from positive dispersion stocks or for the lower value of private information.

[Insert Table 4 About Here]

Short-Selling Measures: We conduct two main tests to evaluate the role of short-sale constraints in the returns exhibited by high $\beta \times D$ stocks. First, we proxy for the cost of borrowing shares using the TED spread. We divide our sample into sub-periods based on the beginning of the month level of the TED spread. We download the TED spread, the three month LIBOR minus the three month T-Bill rate, from FRED[23]. Second, we proxy for the supply of shares available for shorting with outstanding short interest, as a percent of shares outstanding. We compute short interest using COMPUSTAT data and divide our sample into cross-sectional sub-samples. In both cases, we divide our sample at the median. High TED spread periods capture above median short-sale costs and high short interest stocks capture a below median supply of shares for borrowing.

[Insert Table 5 About Here]

In Table 5, we show the results for FMB regressions of individual stock returns on $\beta \times D$ variables benchmarked by the FFC. Each column reflects the results for sub-samples defined

[22]We cross-sectionally residualize $D_{i,t}$ on $\beta_{i,t}^{MKT}$ and $\beta^{MKT} \times U_{i,t}$ to reduce collinearity.

[23]The TED spread is discontinued as of 2022, and results reflect only periods in our sample for which the TED spread is available.

by the TED spread or short interest, respectively. We find the estimated price of market risk and the $\beta \times D$ interaction are significant across specifications. In the time-series TED comparison, the FMB price on the interaction does not appear to vary. In the cross-sectional short interest comparison, the price on the interaction insignificantly increases in high short interest stocks. When there is lower supply of shares available to short, arbitrageurs face a friction in applying their private information to resolve overpricing. However, given the insignificance of this friction to our results, we see that short-sale constraints are not a first-order effect.

Comparison with Common Factor Models: Turing to common factor models, we replicate our main result on individual stock returns in the CAPM, the Fama-French three-factors plus momentum model (Carhart (1997)), the Fama-French three-factors plus momentum plus liquidity model (Pástor and Stambaugh (2003)), the Fama-French five-factors model (Fama and French (2016)), the q-factors model (Hou et al. (2015)), and the mispricing factors model (Stambaugh and Yuan (2017))[24]. In Table 6, Panel A shows results excluding the $\beta \times D$ interaction and Panel B shows results including the interaction. Excluding $\beta \times D$, the FMB estimates for the market premium across all models are either insignificant or marginally significant and the pricing errors (FMB intercepts) are positive and significant (t-Stats for intercepts are at least at or above 2.79). Including $\beta \times D$, estimates for the market premium are significant (t-Stats between 3.67 and 4.62) and consistent with the observed premium, intercepts are insignificant, and the $\beta \times D$ interaction is significant and negative (t-Stats between -4.68 and -5.48). We omit the estimated prices of the additional risk factors from each model in Table 6 for brevity; though, we note that the inclusion of the $\beta \times D$ interaction does not change the direction of point estimates in any model and marginally affects significance.

[Insert Table 6 About Here]

[24]We end estimation of the mispricing factors model in 2016 based on data availability.

Additional Tests: In the internet appendix, we supplement these results with a battery of robustness tests. Our main results hold using a pooled specification (Appendix Table 1); using daily stock returns benchmarked by factors estimated over the prior year of daily returns (Appendix Table 2); when we split our sample at the midpoint of Oct.-2004 (Appendix Table 3); splitting our sample by analyst coverage (Appendix Table 3); splitting our sample into low and high forecast dispersion stocks (Appendix Table 3); in small and large stocks (Appendix Table 3); or with alternative first-stage rolling windows (Appendix Table 3). We winsorize factor loadings at the 5% and 95% levels to mitigate the effect of outliers. We collect a wide range of firm and risk characteristics (including alternative beta anomaly explanations) and, using these characteristics as controls, find our results are robust (Appendix Table 4).

Similar to our common factor model results, we find our $\beta \times D$ interaction results are unaffected by the inclusion of alternative time-series measures of uncertainty, disagreement, or beta anomaly factors (Appendix Table 5). Finally, our results are similar when estimated using test assets (instead of individual stocks) in our main specification (Appendix Table 9) and common factor models (Appendix Table 10).

5 Investor Heterogeneity

In our model, uninformed investors potentially overvalue (excessive optimism) or undervalue (excessive pessimism) firms when cash flow noise is high. In either case, informed investors will tend to trade in the direction of fundamental value. As an investor's ability or investment technology quality increases, the investor's private estimate of fundamental value converges to the true value. The informed investor, therefore, is short overvalued stocks relative to the positioning of uninformed investors, and vice versa.

We analyze this trading in two contexts: arbitrage trading and intraday vs. overnight returns. First, we test the $\beta \times D$ interaction against the net-arbitrage trading (Chen et al.

(2019) of sophisticated investors. Net-arbitrage trading ("NAT") measures the holdings of hedge funds identified through SEC From 13-F filings against aggregate short interest. Thus, NAT is high (low) when sophisticated arbitrageurs in aggregate identify and trade in the direction of undervaluation (overvaluation). Second, we examine intraday vs. overnight returns. A growing literature has documented the "tug-of-war" (Lou et al. (2019)) in intraday vs. overnight returns between informed and uninformed investors. Hendershott et al. (2020) recover a strongly negative (positive) intraday (overnight) SML, which the authors attribute to beta speculators trading intraday. Lu et al. (2022) provide a theory in which frictions between different types of arbitrageurs give rise to the pattern as fast arbitrageurs attempt to satisfy speculative demand and slow arbitrageurs work to correct mispricing. Thus, high $\beta \times D$ stocks will be overpriced (corrected) during the day (at night) based on the presence in the market of uninformed and informed investors.

Net Arbitrage Trading: We access NAT data from Yong Chen's website, which is available based on 13-F filings from the fourth quarter of 1989. For each stock, NAT is defined as aggregate hedge fund long positions less aggregate short interest where both values are demeaned relative to the trailing four quarters. NAT is expressed as a percent of market capitalization, so that NAT captures the recent directional trading of arbitrageurs relative to the size of each firm. We measure the effects of NAT in the quarter immediately following the period represented in the 13-F filings so that we capture holdings and trade positioning prior to returns. Since (on average) uninformed investors overvalue stocks, we predict that arbitrageurs will increase shorting of high $\beta \times D$ stocks. However, this effect will be mitigated by the cases when uninformed investors undervalue stocks. Thus, we also expect to observe an increase in absolute NAT in high $\beta \times D$ stocks. Finally, we predict the direction of NAT will predict the direction of returns in high $\beta \times D$ stocks. That is, sophisticated arbitrageurs will correctly position trades long or short in high $\beta \times D$ stocks.

We present our results in Table 7. In Panel A, we correlate NAT activity with stock-level factor loadings and firm characteristics. We include a vector of firm characteristics relevant to investor demand as controls[25]. First, we examine NAT: in both FMB and fixed effects (firm-by-year FE's) specifications, we find no significant relationship between NAT and $\beta \times D$. In cross-sectional results, market betas are negatively related to NAT consistent with informed investors shorting high beta stocks. Next, we examine |NAT|: we find |NAT| is significantly and positively related to $\beta \times D$ (t-Stats of 7.41 and 3.21 in FMB and fixed effects specifications, respectively). Hence, both long and short activity increases in high $\beta \times D$ stocks.

[Insert Table 7 About Here]

In Panel B, we test individual stock returns based on NAT interacted with $\beta \times D$. Tests include FFC factor loadings and the $\beta \times D$ interaction as controls. If sophisticated arbitrageurs place trades in the direction of fundamental value conditional on $\beta \times D$, we would expect to observe positive FMB prices on the interaction of NAT and $\beta \times D$. In FMB specifications, we estimate a positive but insignificant price on the interaction of NAT and $\beta \times D$. The magnitude is about one-third of the main NAT effect. In pooled specifications, the economic effect of the interaction is closer to two-thirds of the main NAT effect and is significant (t-Stats between 3.38 and 3.40). Both results from Panel A and Panel B are consistent with sophisticated arbitrageurs placing directional bets in high $\beta \times D$ stocks that are, on average, towards fundamental value.

Intraday vs. Overnight Returns: If arbitrageurs trade against mispricing in high $\beta \times D$ stocks, the recent literature on intraday vs. overnight returns suggests we should detect low (high) intraday (overnight) returns in high $\beta \times D$ stocks. Differences in returns within the 24-hour cycle must come from differences in the marginal investor across the cycle, rather than differences in risk prices within the cycle. In particular, Lu et al. (2022) provide a model in which uniformed speculators trade at the open and arbitrageurs trade throughout

[25]Controls include the log of market equity, book-to-market ratio, operating profitability, investment, debt-to-equity ratio, 11-1 return and dividend yield. All values are winsorized at the 1% and 99% level. See Appendix A2 for a description of controls.

the day. Fast arbitrageurs (such as market makers or high-frequency traders) can predict order-flow, thus satisfy uninformed demand at the open. Slow arbitrageurs (such as statistical arbitrageurs) respond throughout the day to mispricing. Thus, high $\beta \times D$ stocks will be overvalued at the open (when uninformed investors trade) and will move towards fundamental value at the close (as informed investors correct mispricing).

In Table 8, we turn our attention to FMB regressions on intraday vs. overnight returns. Factor loadings are estimated on 252 days[26] of trailing returns and returns are raw intraday and overnight returns. Loadings are then lagged to the next day to predict returns. Based on the availability of CRSP data, estimates of intraday vs. overnight returns restrict our sample to trading days after June 15, 1992. We report results for FMB estimates using Newey-West standard errors with 10 lags.

[Insert Table 8 About Here]

First, we compare results for intraday returns excluding and including $\beta \times D$. Benchmarking using the market-model (D1) and FFC model (D3), we find results consistent with Hendershott et al. (2020): the intercept is significant and positive (coefficients range from 6.10 bps/day to 6.76 bps/day and t-Stats range from 8.78 to 10.00)[27] and the estimated price market risk is significant and negative (coefficients range from -4.51 bps/day to -7.02 bps/day and t-Stats range from -4.35 to -5.53). When adding $\beta \times D$ (D2 and D4), we find the negative intraday return is almost entirely concentrated in the interaction effect: the estimate price of $\beta \times D$ is significant and negative (coefficients range from -9.05 bps/day to -10.62 bps/day and t-Stats range from -13.24 to -15.55) and the estimated price of market risk is insignificant. The intercepts are insignificant (D2) or marginally significant (D4) and positive, with an economically and meaningfully lower magnitude than the estimate obtained when excluding $\beta \times D$.

[26]We require a minimum of 126 observed returns required for inclusion.

[27]We use "bps/day" to describe the units of coefficients presented, though these coefficients represent returns realized only in the portion of each day analyzed.

Comparing results for overnight returns, we find the pattern is reversed. Excluding $\beta \times D$ (N1 and N3), we find the estimated price of market risk is significant and positive (coefficients range from 3.87 bps/day to 7.31 bps/day and t-Stats range from 6.83 to 12.09). Including $\beta \times D$ (N2 and N4), the estimated price of the interaction term is significant and positive (coefficients range from 5.40 bps/day to 7.54 bps/day and t-Stats range from 16.05 to 18.13) and the estimated price of market risk is significant and positive in the market model (N2) and positive but not significant in the FFC model (coefficients range from 0.65 bps/day to 2.39 bps/day and t-Stats range from 1.08 to 3.83). Including $\beta \times D$, intercepts are significant and positive (coefficients range from 3.19 bps/day to 3.89 bps/day and t-Stats range from 7.02 to 7.93); excluding $\beta \times D$, intercepts are insignificant. This overnight reversal of the conditional SML is consistent with uninformed investors overvaluing high-dispersion stocks, as the positive overnight price of $\beta \times D$ reflects high opening prices for these stocks the next day.

The $\beta \times D$ interaction resolves some puzzling aspects previously document in intraday vs. overnight returns. First, since we regress raw intraday and overnight returns, the intercepts of the FMB regression estimate the risk-free rate in intraday and overnight periods. Excluding $\beta \times D$, the estimated risk-free rate varies widely between intraday (significantly positive) and overnight (insignificant) periods. Including $\beta \times D$, the estimated risk-free rates are significantly positive and economically higher overnight. If the risk-free rate is somewhat higher overnight, this would be consistent with lower liquidity for financial intermediaries overnight.

Second, including $\beta \times D$ recovers an estimated equity premium consistent with the observed market return intraday. Using the SPY S&P 500 ETF to proxy for the intraday and overnight market returns, we estimate an average intraday (overnight) market return of 0.40bps/day (3.90bps/day) with a standard error of 1.12bps/day (0.78bps/day)[28]. Even though we estimate on raw returns, coefficient estimates will still reflect excess return risk

[28]SPY returns are available starting from February 2, 1993; so, we recompute coefficient estimates only for the period with comparable SPY returns to calculate p-values listed in Table 8.

prices (the risk-free rate estimate is absorbed by the intercept), so the SPY return will be an upwardly biased proxy for our p-value test. With this caveat, we find the estimated intraday price of market risk is not (is) significantly different from the SPY return when including (excluding) $\beta \times D$ (p-values of 63.7% and 81.9% when including and 0.0% and 0.2% when excluding). Overnight, the two-factor $\beta \times D$ model (N2) and the FFC (without $\beta \times D$) (N3) recover the SPY return with p-values of 10.6% and 91.2%, respectively. The market model estimate excluding $\beta \times D$ (N1) is significantly higher (p-value of 0.1%) than the SPY return and the FFC with $\beta \times D$ estimate (N4) is significantly lower (p-value of 0.1%). Overall, we conclude that the inclusion of $\beta \times D$ in intraday vs. overnight FMB tests recovers more reasonable estimates of the risk-free rate and the equity premium while absorbing a substantial portion of the variation between intraday and overnight returns associated with uninformed demand.

6 Market Events

Our model does not explicitly introduce time-series dynamics to dispersion, but nevertheless offers intuition for price responses to a changing beliefs distribution. Unlike increases in risk, increases in dispersion increase the market price of the firm's shares. Optimists have high return expectations and optimistic beliefs are weighted in the equilibrium price in proportion to the dispersion level. Conversely, partial resolution of uncertainty decreases the market price by mitigating the effect of belief dispersion. We test potential time-series effects by examining firm earnings and macroeconomic announcements. Earnings announcements represent a partial resolution of firm-level uncertainty and macro announcements provide systematic information.

Firm-Level Earnings-Cycle: We investigate return patterns in the earnings-cycle with event studies on earnings announcement dates. When firms release updated cash flow data, heterogeneity in private valuations across investors partially resolves. Ex-ante, informed investors will demand high returns to hold assets subject to announcement risk (Savor and Wilson (2016)); whereas ex-post, downward revisions in uninformed investors' private valuations will result in low returns for high $\beta \times D$ stocks.

To perform these event studies, we collect earnings announcement dates from IBES. For earnings announcements marked as posted after the market close (4:00PM ET), we set the event date to the day after the earnings announcement. We test an event window of t = [-5,5] around the earnings event for each stock in our sample. Factor loadings are estimated on 252 days of trailing returns (with a minimum of 126 observed returns) and lagged 50 days prior to the event window. $\beta_{i,t-1} \times D_{i,t-1}$'s are estimated using the firm's dispersion measured at the prior earnings announcement. We measure abnormal returns in the event window benchmarked by the FFC and a modified DGTW (Daniel et al. (1997)) benchmark. To construct our modified DGTW benchmark returns, we match stocks to portfolios by sorting on market beta (quintiles), dispersion (quintiles), size (3-4-3 decile groupings), and value (3-4-3 decile groupings). We test returns by sorting stocks into dispersion quintiles and comparing low (Q1) and high (Q5) stocks and by benchmarking with the FFC model including the $\beta \times D$ interaction. For the latter test, we regress abnormal returns on market betas and $\beta \times D$ interacted with event-day fixed effects, as follows:

$$\hat{e}_{i,k,t} = \delta_0 + \delta_{1,t} + \delta_{2,t}\hat{\beta}^{MKT}_{i,k} + \delta_{3,t}(\beta \times D)_{i,k} + \vec{\delta_4} \cdot \vec{\hat{\beta}}^{FFC}_{i,k} + \varepsilon_{i,k,t} \tag{25}$$

for stock i in earnings event k on event date t where $\vec{\hat{\beta}}^{FFC}_{i,k}$ is the vector of FFC factor loadings. Standard errors are clustered by event.

In Table 9, we show event day results for abnormal returns computed using the FFC. Comparing low (Q1) and high (Q5) dispersion stocks, both groups earn positive and significant abnormal returns prior to the event day. On the event day, Q1 stocks earn a large positive and significant abnormal returns (coefficient of 18.84 bps with a t-Stat of 6.48) and Q5 stocks earn a large negative and significant abnormal returns (coefficient of -38.63 bps with a t-Stat of -8.36). Both groups realize little significant abnormal returns following the event day, but the coefficient estimates following the event day continue in the same direction as the event day return. Cumulatively, Q1 stocks earn a 67.72 bps (t-Stat: 11.25) abnormal return in the 10-day window immediately around the earnings date and Q5 stocks earn a -34.04 bps (t-Stat: -3.31) abnormal return.

[Insert Table 9 About Here]

Our interaction test shows that pre-announcement abnormal returns are unrelated to $\beta \times D$ whereas event day returns are significantly related to market risk and $\beta \times D$ loadings. On the event day, market betas predict a 24.67 bps (t-Stat: 4.77) abnormal return and the $\beta \times D$ interaction predicts a -53.31 bps (t-Stat: -10.09) abnormal return. The large positive abnormal return correlated with market betas is consistent with informed investors demanding high returns ex-ante to compensate for announcement risk. The large negative abnormal return attributable to $\beta \times D$ is consistent overvaluation in high $\beta \times D$ stocks that is partially resolved by uncertainty resolution on the event day. Cumulatively, abnormal returns correlated with market betas (coefficient of 34.90 bps; t-Stat of 2.93) and $\beta \times D$ (coefficient of -99.48 bps and a t-Stat of -8.38) persist in the 10-day window and the uncorrelated return reverses by the end of the event window. The former is due to a modestly negative post-announcement drift that may reflect slow adjustment of beliefs conditional on earnings information.

In Appendix Table 8, we repeat this analysis using our modified DGTW benchmark to compute abnormal returns. We believe using a modified benchmark is appropriate since the $\beta \times D$ interaction is highly significantly priced in the cross-section of returns. Benchmarking with stocks of similar dispersion levels controls for the average mispricing in the stock market correlated with $\beta \times D$. We find that when using modified DGTW benchmarks to account for $\beta \times D$, the significance of our results remains but the magnitudes are decreased by up to two-thirds. In Appendix Figure 2, we plot cumulative abnormal returns in the event window for our interaction test based on both the FFC and modified DGTW benchmarks, which visually demonstrates the extent to which cumulative abnormal returns may be biased away from zero without controlling for the $\beta \times D$ interaction.

Macro Announcements: Savor and Wilson (2014) identify a macro announcement beta anomaly in which the CAPM works well on announcement days but not on non-announcement days. The authors argue it is difficult to reconcile a linear factor model with the return patterns observed on announcement and non-announcement days. In order for such models to aggregate over mutually exclusive time periods, linear factor models need to successfully price returns in each time period (i.e., the factor structure cannot be of different on different types of days).

We repeat the main FMB tests of Savor and Wilson (2014) including the $\beta \times D$ interaction. Announcement days include all days during our sample period (Aug. 1986-Dec. 2022) with FOMC meetings[29] or Bureau of Labor Statistics employment or producer price statistics releases. We identify 1,138 announcement days and 8,041 non-announcement days. In Table 10, we estimate regressions of individual stock returns on lagged factor loadings separately for announcement and non-announcement days. Columns (A1)-(A4) show results on announcement days for the market model and FFC model (including / excluding the $\beta \times D$ interaction factor) and (N1)-(N4) show comparable results for non-announcement days. On announcement days, the estimated market price of risk is significantly priced across specifications (coefficients range from 9.62 bps/day to 13.32 bps/day and t-Stats range from 2.49 to 3.28) reflecting the high market returns on announcement days (p-values for comparing our FMB estimates to the in-sample market return range from 36.3% to 96.9%). For $\beta \times D$, the estimate benchmarked by the FFC model is significant (coefficient is -3.59 bps/day with a t-Stat of -2.89) and the estimate benchmarked by the market model is marginally significant but economically consistent (coefficient is -2.66 bps/day with a t-Stat of -1.64).

[Insert Table 10 About Here]

[29]The date tested is policy announcements on the final day of the meeting

On non-announcement days, the market premium is positive only when including $\beta \times D$. In (N2) and (N4) we find coefficient estimates for the price of market risk of 1.89bps/day and 1.72bps/day when benchmarking by the market model and FFC model, respectively. Neither estimate is significant; however, given the low market returns on non-announcement days these coefficients are consistent with observed market returns (p-values of 75.2% and 67.4%, respectively). When excluding $\beta \times D$ (N1 and N3), the point estimates for the FMB price of market risk are negative on non-announcement days.

In particular, $\beta \times D$ is highly significant on non-announcement days: coefficients are -4.19 bps/day with a t-Stat of -6.68 (market model) and -4.50b bps/day with a t-Stat of -9.54 (FFC). Economically, results for $\beta \times D$ are consistent across the two types of days. Our interpretation of these results is that macro announcement days reveal systematic information relevant for the equity market as a whole; whereas, $\beta \times D$ captures disagreement at the firm-level across both types of days. Including $\beta \times D$ recovers an estimated equity premium consistent with the observed market return on both types of days; thus, we conclude $\beta \times D$ is the omitted variable needed to aggregate returns across different types of days.

7 Conclusion

Our parsimonious solution to the beta anomaly resolves many of the puzzling findings presented in recent asset pricing "tales." Studying the beta anomaly is different from many problems in empirical finance because we know what the correct answer should be: the estimated price of market risk should equal the observed market return. In a variety of scenarios and benchmarking by conventional factor models, we find that including an interaction variable of risk exposure and investor disagreement ($\beta \times D$) in FMB tests produces point estimates consistent with the market return. The $\beta \times D$ interaction is highly significantly priced in its own right and the inclusion of $\beta \times D$ is consistent with a complete cross-sectional asset pricing model (intercepts are insignificant). We interpret our main results as strong evidence that trading induced by high firm-level dispersion is important for stock prices and the resulting mispricing is increasing in market beta. Investors have the CAPM in mind when they attempt to price assets (Berk and van Binsbergen (2016)); thus, conditional on $\beta \times D$, investors demand high returns to hold market risk. Optimistic investors err in estimating the future cash flows available to investors when uncertainty is high and empirically (it turns out) the market beta magnifies such errs.

There are certainty many interesting avenues for future research in $\beta \times D$. The variation of returns in high $\beta \times D$ stocks across the time-series is an issue we ignore here. An empirical question is the extent to which uninformed investors are aware of the level of uncertainty they face in pricing stocks: it is possible the high price paid by retail investors for active mutual fund management is more reasonable when $\beta \times D$ is accounted for. If investors are paying active managers to rent their private information, we may observe low returns to active strategies when managers buy high dispersion stocks. Nevertheless, investors may be earning positive alphas relative to their own abilities to trade in high dispersion stocks. Alternatively, the degree to which inefficient financial markets and the real economy interact has attracted increasing attention in recent literature (e.g., Dong et al. (2021), Horstman (2022)), and skilled firm managers potentially have a role to play in high dispersion firms. Finally, benchmarks including $\beta \times D$ can deliver economically different results from conventional return benchmarks. Drift phenomena, including the post-earnings announcement drift, seem ripe for studying in this framework.

References

A. Ang, J. Lui, and K. Schwarz. Using stocks or portfolios in tests of factor models. *Journal of Financial and Quantitative Analysis*, 55(3):709–750, 2019.

M. Baker, B. Bradley, and J. Wurgler. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal*, 67:1–15, 2011.

T.G. Bali, S.J. Brown, S. Murray, and Y. Tang. A lottery-demand-based explanation of the beta anomaly. *Journal of Financial and Quantitative Analysis*, 52(6):2369–2397, 2017a.

T.G. Bali, S.J. Brown, and Y. Tang. Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics*, 126:471–489, 2017b.

O.E. Barron, O. Kim, S.C. Lim, and D.E. Stevens. Using analysts' forecasts to measure properties of analysts' information environment. *Accounting Review*, 73(4):421–433, 1998.

J.B. Berk and J.H. van Binsbergen. Assessing asset pricing models using revealed preference. *Journal of Financial Economics*, 119:1–23, 2016.

F. Black. Capital market equilibrium with restricted borrowing. *Journal of Business*, 45(3): 444–454, 1972.

M.M. Carhart. On persistence in mutual fund performance. *Journal of Finance*, 52(1):57–82, 1997.

Y. Chen, Z. Da, and D. Huang. Arbitrage trading: The long and the short of it. *Review of Financial Studies*, 32(4):1608–1646, 2019.

Y. Chen, Z. Da, and D. Huang. Short selling efficiency. *Journal of Financial Economics*, 145:387–408, 2022.

Zengjing Chen and Larry Epstein. Ambiguity, risk, and asset returns in continuous time. *Econometrica*, 70(4):1403–1443, 2002.

J.H. Cochrane. Presidential address: Discount rates. *Journal of Finance*, 66(4):1047–1108, 2011.

K. Daniel, M. Grinblatt, S. Titman, and R. Wermers. Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 52(3):1035–1058, 1997.

K.B. Diether, C.J. Malloy, and A. Scherbina. Differences of opinion and the cross section of stock returns. *Journal of Finance*, 57(5):2113–2141, 2002.

M. Dong, D. Hirshleifer, and S.H. Teoh. Misvaluation and corporate inventiveness. *Review of Financial Studies*, 25:3645–3683, 2021.

Darrell Duffie, Nicolae Garleanu, and Lasse Heje Pedersen. Securities lending, shorting, and pricing. *Journal of Financial Economics*, 66(2-3):307–339, 2002.

E.F. Fama and K.R. French. The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465, 1992.

E.F. Fama and KR. French. Multifactor explanations of asset pricing anomalies. *Journal of Finance*, 51(1):55–84, 1996.

E.F. Fama and K.R. French. The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives*, 18(3):25–46, 2004.

E.F. Fama and K.R. French. Dissecting anomalies with a five-factor model. *Review of Financial Studies*, 29(1):69–103, 2016.

E.F. Fama and J.D. MacBeth. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636, 1973.

A. Frazzini and L.H. Pedersen. Betting against beta. *Journal of Financial Economics*, 111: 1–25, 2014.

I. Friend and M. Blume. Measurement of portfolio performance under uncertainty. *American Economic Review*, 60(4):561–575, 1970.

M.R. Gibbons, S.A. Ross, and J. Shanken. A test of the efficiency of a given portfolio. *Econometrica*, 57(5):1121–1152, 1989.

S. Giglio and D. Xiu. Asset pricing with omitted factors. *Journal of Political Economy*, 129 (7):1947–1990, 2021.

M. Grinblatt and J. Linnainmaa. Jensen's inequality, parameter uncertainty, and multiperiod investment. *Review of Asset Pricing Studies*, 15:1–34, 2011.

J.M. Harrison and D.M. Kreps. Martingales and arbitrage in multiperiod securities markets. *Journal of Economic theory*, 20(3):381–408, 1979.

M. Hasler and C. Martineau. The capm can predict returns. *Working Paper*, 2021.

T. Hendershott, D. Livdan, and D. Rösch. Asset pricing: A tale of night and day. *Journal of Financial Economics*, 138:635–662, 2020.

H. Hong and D.A. Sraer. Speculative betas. *Journal of Finance*, 71(5):2095–2144, 2016.

D. Horstman. Mispricing and firm investments. *Working Paper*, 2022.

K. Hou, C. Xue, and L. Zhang. Digesting anomalies: An investment approach. *Review of Financial Studies*, 28(3):650–705, 2015.

K. Hou, C. Xue, and L. Zhang. Replicating anomalies. *Review of Financial Studies*, 33(5): 2019–2133, 2020.

D. Jeong, H. Kim, and J.Y. Park. Does ambiguity matter? estimating asset pricing models with a multiple-priors recursive utility. *Journal of Financial Economics*, 115(2):361–382, 2015.

K. Jurado, S.C. Ludvigson, and S. Ng. Measuring uncertainty. *American Economic Review*, 105(3):1177–1216, 2015.

P. Jylhä. Margin requirements and the security market line. *Journal of Finance*, 73(3): 1281–1321, 2018.

D. Lou, C. Polk, and S. Skouras. A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, 134:192–213, 2019.

Z. Lu, S. Malliaris, and Z. Qin. Fast and slow arbitrageurs: Implications for return predictability. *Working Paper*, 2022.

L. Pástor and R.F. Stambaugh. Liquidity risk and expected stock returns. *Journal of Political Economy*, 111(3):642–685, 2003.

P. Savor and M. Wilson. Asset pricing: A tale of two days. *Journal of Financial Economics*, 113:171–201, 2014.

P. Savor and M. Wilson. Earnings announcements and systematic risk. *Journal of Finance*, 71(1):83–138, 2016.

R.F. Stambaugh. On the exclusion of assets from tests of the two-parameter model. *Journal of Financial Economics*, 10:237–268, 1982.

R.F. Stambaugh and Y. Yuan. Mispricing factors. *Review of Financial Studies*, 30(4): 1270–1315, 2017.

R.F. Stambaugh, J. Yu, and Y. Yuan. Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance*, 70(5):1903–1948, 2015.

Tables & Figures

Figure 1A: Beta x Forecast Dispersion Test Assets, Monthly

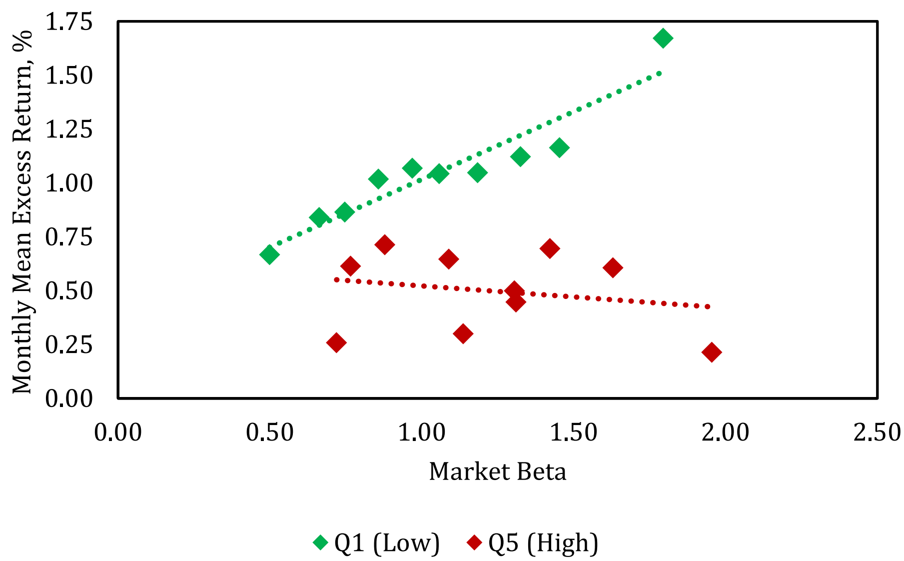
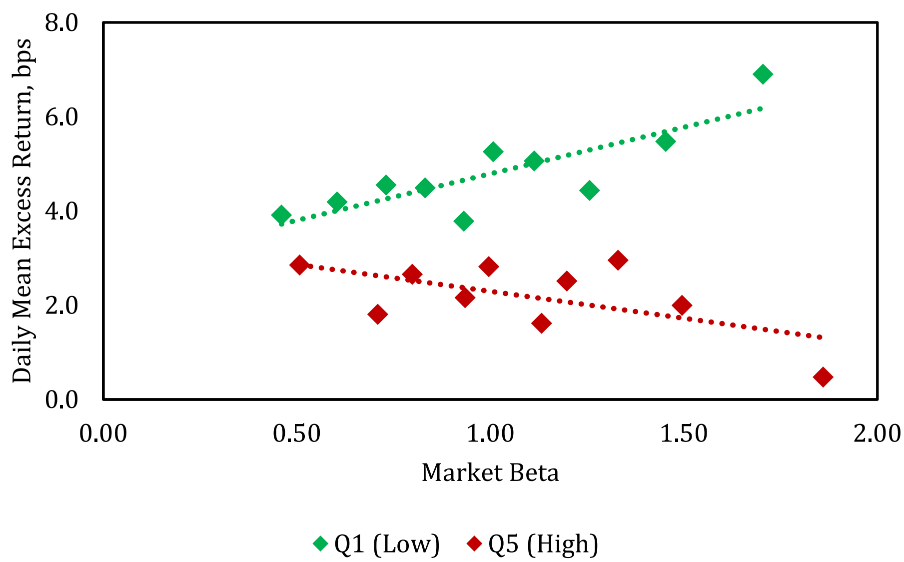
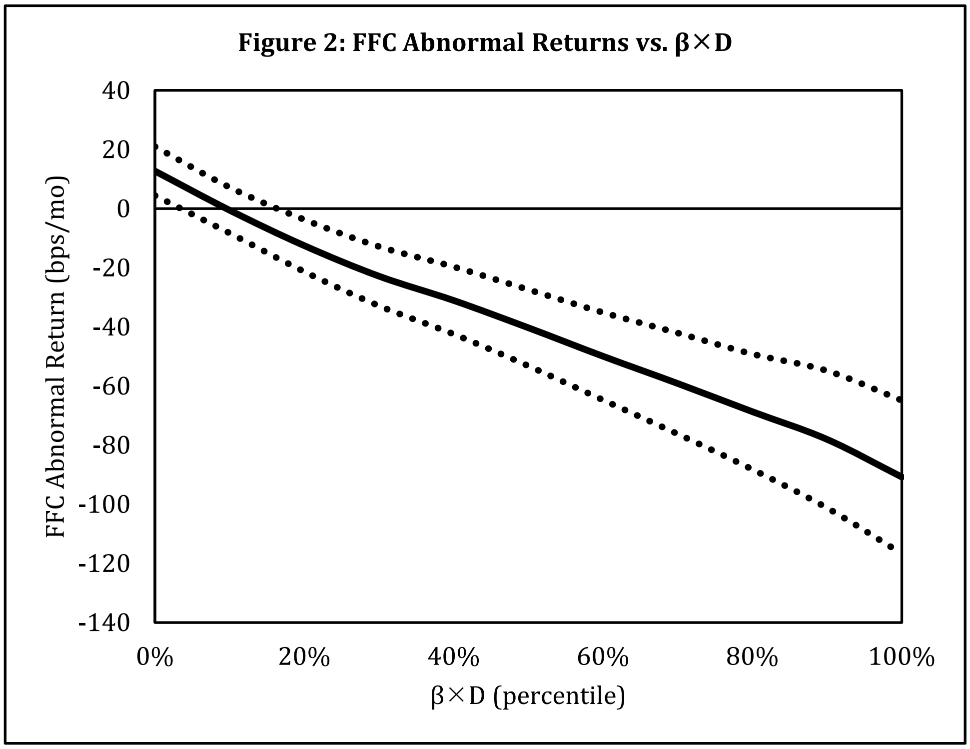


Figure 1B: Beta x Forecast Dispersion Test Assets, Daily



Note: Mean excess returns for twenty (ten "high" and ten "low") beta decile test assets contstructed on analysts' forecast dispersion quintiles. Q1 (green) test assets include stocks from the bottom quintile of forecast dispersion and Q5 (red) test assets from the top. Test assets are constructed monthly based on the prior month's stock-level market beta and dispersion using simultaneous sorting. In Figure 1A, stock-level betas are computed using rolling 60 mo. windows (min. 30 observations). In Figure 1B, stock-level betas are computed using rolling 252 day windows (min. 126 obs.). Test asset returns are value-weighted. The sample period is Aug. 1986-Dec. 2022. Dotted lines are SMLs fitted from regressions of full sample mean returns on full sample market betas, computed using monthly (1A) and daily (1B) data, respecitvely.



Note: Mean monthly FFC abnormal returns attributable to the β×D interaction for individual stocks, plotted by percentile of the population ranked by β×D. We estimate the distribution function each month based on lagged factor loadings following Stambaugh, Yu, and Yuan (2015), then average the estimate over the sample period via the Fama-MacBeth procedure. The sample period is Aug. 1986-Dec 2022. Dotted lines represent 90%-confidence intervals.

Table 1: Mean Monthly Excess Returns vs. Market Betas

Characteristic Decile × Forecast Dispersion Quintile Test Assets, Value Weighted

Security Market Line (SML) Coefficients (*t*-Stats)

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Beta	**0.63**	**0.59**	0.09	0.13	-0.10	**-0.73**
	(7.63)	**(3.23)**	(1.39)	(1.65)	(-0.62)	**(-3.95)**
Alpha	**0.81**	**0.68**	0.38	0.22	**-0.48**	**-1.29**
	(3.53)	**(3.09)**	(0.65)	(0.85)	**(-2.54)**	**(-4.34)**
Ivol	**0.88**	**0.65**	0.03	0.36	**-0.50**	**-1.38**
	(5.02)	**(4.40)**	(0.15)	(1.20)	**(-2.01)**	**(-4.53)**
Momentum	0.06	0.39	-0.09	-0.03	**-0.80**	-0.86
	(0.16)	(1.30)	(-0.50)	(-0.05)	**(-3.27)**	(-2.00)
Size	**2.03**	**1.17**	**0.57**	**0.69**	**-1.17**	**-3.20**
	(5.20)	**(3.89)**	**(3.09)**	**(2.75)**	**(-2.56)**	**(-5.32)**
Value	**1.87**	-0.11	**-0.74**	**-1.04**	**-1.68**	**-3.55**
	(4.50)	(-0.30)	**(-3.30)**	**(-2.01)**	**(-2.06)**	**(-3.88)**
Profitability	**0.91**	0.58	0.24	-0.52	-1.00	**-1.91**
	(3.28)	(1.54)	(0.97)	(-1.40)	(-1.73)	**(-2.98)**
Investment	0.87	-0.79	-0.70	-1.07	-1.28	**-2.15**
	(2.00)	(-1.62)	(-1.67)	(-1.92)	(-1.49)	**(-2.23)**
All	**0.71**	**0.57**	0.07	0.13	**-0.52**	**-1.23**
	(8.55)	**(7.19)**	(0.97)	(1.33)	**(-4.82)**	**(-9.05)**

Note: Results for OLS regressions of full sample mean monthly excess returns on full sample market betas for 400 test assets, formed by simultaneously sorting on eight characteristics (deciles) and analysts' forecast dispersion (quintiles). There are 50 test assets formed on each characteristic and returns are value weighted. Characteristics tested are market beta, alpha (computed using the Fama-French-Carhart (FFC) model), ivol (computed using the FFC model), momentum, size, value, profitability, and investment. Momentum, value, profitability, and investment test assets are formed on the NYSE breakpoints available on Kenneth French's website. Otherwise, we sort into characteristic deciles based on our sample. For size, we sort based on our sample due to the relatively low number of small stocks with valid analysts' forecast data. Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. Stocks are sorted into month *t+1* portfolios based on factor loadings and characteristics computed using data up to month *t*. See Appendix A1 for a description of test asset construction. *t* -Stat are reported in parentheses and computed using OLS standard errors. |*t*-Stats| > 2.00 are indicated in **bold**.

Table 2: Sample Statistics

Panel A: Sample & Analyst Coverage by Year

	CRSP Universe			IBES Sample		
Date	Firms (*count*)	Size (*mean, $MM*)	IBES Sample (*%*)	Firms (*count*)	Size (*mean, $MM*)	Analysts (*mean*)
02/1984	5,736	307.6	3.4	195	2,435.3	4.7
12/1985	5,791	345.6	15.1	873	1,517.2	4.4
12/1990	5,746	466.5	29.5	1,693	1,444.4	5.7
12/1995	7,009	890.7	28.3	1,987	2,692.2	4.2
12/2000	6,439	2,192.6	49.7	3,202	4,225.7	6.6
12/2005	4,792	3,096.7	60.7	2,911	4,954.4	7.9
12/2010	3,983	3,410.8	67.7	2,698	4,926.9	8.9
12/2015	3,781	5,847.0	73.1	2,763	7,888.4	9.0
12/2020	3,751	9,966.3	72.9	2,733	13,375.4	8.0
12/2022	4,404	9,200.9	69.6	3,066	12,965.6	7.6

Panel B: IBES Sample vs. CRSP Universe vs. Ex-IBES Sample, Monthly Means

	CRSP Universe	IBES Sample	Ex-IBES Sample
Firms (*count*)	5,193	2,286	2,907
Size (*mean, $MM*)	3,167.3	5,148.8	268.8
Monthly Excess Returns			
Mean, E(R)	0.70	0.71	0.57
Std Dev, σ(R)	4.52	4.54	4.65

Panel C: IBES Sample Membership

	In CRSP	In IBES Sample	%
Months (*mean*)	151.8	92.6	61.0
Size (*mean, $MM*)	3,739.3	5,148.8	
Monthly Excess Returns			
Mean, E(R)	0.71	0.71	
Std Dev, σ(R)	4.53	4.54	

Note: "IBES Sample" reflects firm-month observations included in our main tests. The sample period is Feb. 1984-Dec. 2022 and firms must have at least two valid analyst estimates available at the firm's most recent earnings announcement date for inclusion. Panel A compares CRSP to our sample at the beginning of our sample and at five-year increments within our sample. Statistics are averages at each period listed. "IBES Sample (%)" is the percentage of CRSP firms appearing in our sample. Panel B compares firm-month observations in our sample to firm-month observations in CRSP but outside of our sample. Statistics are aggregated to each month, then averaged across the sample period. Panel C analyzes all firm-month observations for firms that appear at any point in our sample. "In CRSP" shows statistics for the CRSP lifetime of sample firms and "In IBES" shows statistics for the same set of firms only for the months the firms appear in our sample. All return statistics are value-weighted.

Table 3: Fama-MacBeth Regressions, Individual Stock Monthly Returns vs. Factor Loadings								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**0.58**	0.24	**0.60**	0.25	**0.54**	0.18	**0.55**	0.20
	(2.79)	(1.04)	**(2.88)**	(1.12)	**(2.94)**	(0.88)	**(3.03)**	(0.96)
MKT	0.26	**0.63**	0.24	**0.61**	0.26	**0.64**	0.25	**0.63**
	(1.40)	**(4.04)**	(1.35)	**(3.92)**	(1.57)	**(4.62)**	(1.55)	**(4.55)**
β×D		**-0.62**		**-0.65**		**-0.65**		**-0.65**
		(-4.83)		**(-5.94)**		**(-5.48)**		**(-5.90)**
SMB					0.02	0.05	0.02	0.05
					(0.27)	(0.58)	(0.28)	(0.56)
HML					0.10	0.11	0.09	0.11
					(0.98)	(1.14)	(0.92)	(1.11)
UMD					-0.20	**-0.23**	-0.20	**-0.23**
					(-1.90)	**(-2.29)**	(-1.96)	**(-2.30)**
DMA			0.09	**0.16**			0.14	**0.21**
			(1.35)	**(3.92)**			(1.28)	**(2.04)**
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	437	437	437
Adj. R2	2.5%	3.1%	3.3%	3.7%	4.8%	5.2%	5.2%	5.6%
p(MKT:λ=R)	14.8%	86.8%	11.8%	80.2%	12.1%	89.3%	12.1%	89.3%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for individual stocks. Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β× D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. "DMA" is the analysts' forecast dispersion anomaly, tested as the factor loadings on a long-short portfolio of high vs. low dispersion stocks (Diether et al., 2002). See Appendix A1 for detail on construction of the DMA factor. *t*-Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Table 4: Forecast Dispersion Proxies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.18	0.17	-0.12	-0.16	-0.14	-0.03	-0.04
	(0.88)	(0.80)	(-0.61)	(-0.76)	(-0.68)	(-0.14)	(-0.18)
MKT	**0.64**	**0.65**	**0.63**	**0.63**	**0.61**	**0.61**	**0.59**
	(4.62)	**(4.64)**	**(4.51)**	**(4.53)**	**(4.42)**	**(4.35)**	**(4.24)**
β×D	**-0.65**	**-0.66**	**-0.63**	**-0.64**	**-0.63**	**-1.04**	**-1.09**
	(-5.48)	**(-5.48)**	**(-5.35)**	**(-5.36)**	**(-5.33)**	**(-5.07)**	**(-5.29)**
D		**-0.79**		**-0.85**	**-2.04**		**-2.22**
		(-3.12)		**(-3.37)**	**(-3.32)**		**(-3.63)**
σ(D)			**1.94**	**2.06**	**2.01**	**1.47**	**1.49**
			(3.69)	**(3.98)**	**(3.90)**	**(3.06)**	**(3.20)**
D*σ(D)					**6.90**		**7.82**
					(2.41)		**(2.76)**
β×D*σ(D)						**2.59**	**2.95**
						(3.02)	**(3.52)**
Model	FFC	FFC	FFC	FFC	FFC	FFC	FFC
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	437	437
Adj. R2	5.2%	5.4%	5.4%	5.5%	5.6%	5.5%	5.8%
p(MKT:λ=R)	89.3%	90.8%	84.0%	85.4%	80.7%	78.1%	73.9%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for individual stocks. Fama-French-Carhart (FFC) factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. D and σ (I are the level and volatility (in the first stage rolling window) of our forecast dispersion measure. To reduce collinearity, we cross-sectionally residualize D each month on β and β×D prior to the second stage regression. *t*-Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold.** Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Table 5: Short Sale Constraints

	TED Spread		Short Interest	
	< Median	≥ Median	< Median	≥ Median
Intercept	0.48	-0.06	-0.04	0.30
	(1.95)	(-0.23)	(-0.16)	(1.49)
MKT	**0.44**	**0.88**	**0.71**	**0.52**
	(2.89)	**(4.19)**	**(4.76)**	**(3.54)**
β×D	**-0.60**	**-0.71**	**-0.74**	**-0.49**
	(-3.59)	**(-3.91)**	**(-4.81)**	**(-3.52)**
Model	FFC	FFC	FFC	FFC
SE's	FMB	FMB	NW(6)	NW(6)
T (Mos.)	215	211	437	437
Adj. R2	4.7%	5.8%	5.4%	5.5%
p(MKT:λ=R)	32.5%	67.3%	91.3%	55.5%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for individual stocks. Fama-French-Carhart (FFC) Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. "TED Spread" seperates our sample based on the beginning of the month level of the TED Spread (3 mo. LIBOR minus 3 mo. T-Bill rates, downloaded from https://fred.stlouisfed.org/series/TEDRATE). High TED spreads proxy for high short-selling costs. "Short Interest" seperates our sample each month based on the stock-level of shares sold short relative to shares outstanding from the COMPUSTAT monthly short interest file. Short sale data is lagged one month. *t*-Stats are reported in parentheses and computed using Fama-MacBeth (FMB) or Newey-West (NW) standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Table 6: Price of Market Risk in Factor Models						
	Market Model	FF Three-Factors + Momentum	FF Three-Factors + Momentum + Liquidity	FF Five Factors	Q Factors	Mispricing Factors
Panel A: w/o β ×D Interaction						
Intercept	**0.58**	**0.54**	**0.54**	**0.53**	**0.58**	**0.61**
	(2.79)	**(2.94)**	**(2.98)**	**(2.82)**	**(2.97)**	**(2.83)**
MKT	0.26	0.26	0.25	0.28	0.26	0.21
	(1.40)	(1.57)	(1.58)	(1.68)	(1.63)	(1.19)
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	365
Adj. R2	2.5%	4.8%	5.1%	5.1%	4.9%	4.9%
p(MKT:λ=R)	14.8%	12.1%	11.3%	14.9%	11.7%	14.7%
Panel B: w/ β ×D Interaction						
Intercept	0.24	0.18	0.19	0.16	0.25	0.28
	(1.04)	(0.88)	(0.93)	(0.78)	(1.11)	(1.15)
MKT	**0.63**	**0.64**	**0.63**	**0.68**	**0.62**	**0.57**
	(4.04)	**(4.62)**	**(4.60)**	**(4.59)**	**(4.47)**	**(3.67)**
β×D	**-0.62**	**-0.65**	**-0.64**	**-0.66**	**-0.64**	**-0.64**
	(-4.83)	**(-5.48)**	**(-5.48)**	**(-5.35)**	**(-5.29)**	**(-4.68)**
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	365
Adj. R2	3.1%	5.2%	5.5%	5.5%	5.3%	5.3%
p(MKT:λ=R)	86.8%	89.3%	85.1%	99.4%	83.2%	82.4%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for individual stocks. Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. We compute loadings seperately for various common factor models. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. *t*-Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Table 7: Net Arbitrage Trading

Panel A: Trading Activity Correlated with βxD

	NAT		|NAT|	
	FMB	Firm×Year FE	FMB	Firm×Year FE
MKT	**-0.09**	0.02	**-0.12**	0.04
	(-2.29)	(0.32)	**(-2.20)**	(0.93)
β×D	0.04	0.04	**0.55**	**0.08**
	(0.75)	(0.93)	**(7.41)**	**(3.21)**
D	0.18	0.10	**0.72**	0.12
	(1.56)	(0.96)	**(6.70)**	(1.86)
Controls	Yes	Yes	Yes	Yes
SE's	NW(24)	Cl(Firm×Year)	NW(24)	Cl(Firm×Year)
N (Obs.)	321,000	321,000	321,000	321,000
Adj. R2	2.3%	55.1%	12.1%	62.2%

Panel B: Individual Stocks & NAT

	FMB		Pooled	
	(F1)	(F2)	(P1)	(P2)
NAT	**0.83**	**0.82**	**0.99**	**0.99**
	(6.23)	**(6.22)**	**(3.26)**	**(3.28)**
NAT*β×D	0.23	0.29	**0.70**	**0.69**
	(0.96)	(1.13)	**(3.40)**	**(3.38)**
NAT*D		0.46		0.12
		(0.42)		(0.21)
Model	FFC + β×D	FFC + β×D	FFC + β×D	FFC + β×D
SE's	NW(6)	NW(6)	Cl(Mo.)	Cl(Mo.)
T (Mos.)	312	312	312	312
Adj. R2	6.7%	6.9%	0.1%	0.1%

Note: Results for Fama-MacBeth, pooled, and firm×year fixed effects regressions. Panel A gives results for regressing net abribtrage trading ("NAT" from Chen, Da, and Huang, 2019) and |NAT| on stock-level factor loadings and controls. See Appendix A2 for detail on firm-level controls. NAT is the difference between aggregate hedge funds' 13F long positions and aggregate short sales, expressed relative to total shares outstanding and demeaned over the trailing four quarters. NAT is available between Jan. 90-Dec. 15 and is downloaded from Yong Chen's website. The β×D interaction is found by multiplying the stock-level market beta and analysts' forecast dispersion. We cross-sectionally demean the interaction each month prior to the second-stage regression. Panel B gives results for regressing monthly excess returns on factor loadings & factor interactions with NAT. Prior to the second-stage regression, "D" is cross-sectionally residualized each month on β and β×D. Panel B controls for Fama-French-Carhart (FFC) factor loadings and β×D variables. In both panels, t -Stats are reported in parentheses and computed using Newey-West standard errors with twenty-four (A) or six (B) months of lags (FMB) or clustered by month (pooled) or firm (firm×year fixed effects). |t -Stats| > 2.00 are indicated in **bold**. Adjusted R2 values computed using the FMB procedure for FMB results.

Table 8: Intraday vs. Overnight Returns

	Intraday Returns				Overnight Returns			
	(D1)	(D2)	(D3)	(D4)	(N1)	(N2)	(N3)	(N4)
Intercept	**6.76**	0.92	**6.10**	1.24	-0.44	**3.89**	0.20	**3.19**
	(8.78)	(1.01)	**(10.00)**	(1.66)	(-1.05)	**(7.93)**	(0.50)	**(7.02)**
MKT	**-7.02**	-0.39	**-4.51**	0.68	**7.31**	**2.39**	**3.87**	0.65
	(-5.53)	(-0.34)	**(-4.35)**	(0.65)	**(12.09)**	**(3.83)**	**(6.83)**	(1.08)
β×D		**-10.62**		**-9.05**		**7.54**		**5.40**
		(-13.24)		**(-15.55)**		**(18.13)**		**(16.05)**
Model	MM	MM	FFC	FFC	MM	MM	FFC	FFC
SE's	NW(10)	NW(10)	NW(10)	NW(10)	NW(10)	NW(10)	NW(10)	NW(10)
T (Days)	7,694	7,694	7,694	7,694	7,694	7,694	7,694	7,694
Adj. R2	2.7%	3.0%	6.3%	6.5%	1.6%	1.7%	2.7%	2.8%
p(MKT:λ=R)	0.0%	63.7%	0.2%	81.9%	0.1%	10.6%	91.2%	0.1%

Note: Results for Fama-MacBeth regressions of intraday versus overnight returns on factor loadings for individual stocks. Returns are expressed in basis points. Factor loadings are computed in a first stage regression using 252 day rolling windows. We require a minimum of 126 return observations for a stock to be included. In the second stage, day *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending on day *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. Fama-MacBeth estimates are seperate for intraday and overnight returns. *t* Stats are reported in parentheses and computed using Newey-West standard errors with ten days of lags. |*t*-Stats| > 2.00 are indicated in **bold** Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample SPY (S&P 500 ETF) mean return. SPY data is available from 02/02/93 and we recompute coefficients to correspond for this availability to compare.

Table 9: Event Windows around Earnings Announcement Dates

Event Day	w/i Dispersion		Benchmarked		
	Q1	Q5	Intercept	MKT	β×D
-5	**4.65**	-1.54	0.96	0.14	**-4.80**
	(4.77)	(-0.94)	(0.48)	(0.07)	**(-2.48)**
-4	2.61	4.09	-1.92	4.58	0.79
	(1.45)	(1.41)	(-0.54)	(1.29)	(0.23)
-3	**5.57**	**6.53**	1.73	2.20	-2.20
	(3.32)	**(2.25)**	(0.49)	(0.62)	(-0.65)
-2	**6.46**	**8.85**	3.22	-0.09	-0.96
	(3.84)	**(3.07)**	(0.90)	(-0.03)	(-0.28)
-1	**11.04**	**11.23**	5.15	3.36	-1.13
	(6.36)	**(3.77)**	(1.44)	(0.96)	(-0.32)
0	**18.74**	**-38.63**	**-19.19**	**24.67**	**-53.31**
	(6.48)	**(-8.62)**	**(-3.68)**	**(4.77)**	**(-10.09)**
1	**8.30**	**-12.48**	-5.29	**7.78**	**-20.07**
	(4.28)	**(-3.86)**	(-1.36)	**(2.03)**	**(-5.21)**
2	1.35	**-8.36**	1.41	-0.23	-6.34
	(0.79)	**(-2.81)**	(0.40)	(-0.07)	(-1.84)
3	2.37	-2.18	2.68	-1.60	-3.09
	(1.40)	(-0.75)	(0.77)	(-0.47)	(-0.88)
4	1.92	-0.75	6.19	-4.57	-1.84
	(1.16)	(-0.25)	(1.74)	(-1.33)	(-0.54)
5	**4.71**	-0.79	6.28	-1.32	-6.54
	(2.86)	(-0.28)	(1.82)	(-0.39)	(-1.95)
[-5,5]	**67.72**	**-34.04**	1.23	**34.90**	**-99.48**
	(11.25)	**(-3.38)**	(0.10)	**(2.93)**	**(-8.38)**
Model	FFC	FFC	FFC		
SE's	Cl(Event)	Cl(Event)	Cl(Event)		
Events	66,780	55,725	310,811		

Note: Results for event studies of abnormal returns for individual stocks in the [-5,5] event window around earnings announcement dates. Returns are expresses in basis points. Abnormal returns are computed with respect to Fama-French-Carhart (FFC) factor loadings. Factor loadings are computed in a first stage regression using 252 day rolling windows. We require a minimum of 126 return observations for a stock to be included. Loadings are lagged 50 days prior to the start of the event window. The β×D interaction is found by multiplying the stock-level market beta and analysts' forecast dispersion, where forecast dispersion is computed using data on each firms's prior earnings announcement. We cross-sectionally demean the interaction each month prior to the second stage regression. *t*-Stats are reported in parentheses and computed using standard errors clustered by events. |t-Stats| > 2.00 are indicated in **bold**.

Table 10: Fama-MacBeth Regressions, Macroeconomic Announcement Days

	(A1)	(A2)	(A3)	(A4)	(N1)	(N2)	(N3)	(N4)
	Announcement Days				Non-Announcement Days			
Intercept	-0.42	-1.43	0.23	-1.55	**4.10**	**1.99**	**3.86**	**1.52**
	(-0.24)	(-0.82)	(0.17)	(-1.01)	**(5.35)**	**(2.47)**	**(6.68)**	**(2.43)**
MKT	**12.16**	**13.32**	**9.62**	**11.56**	-0.49	1.89	-0.75	1.72
	(2.92)	**(3.28)**	**(2.49)**	**(2.94)**	(-0.31)	(1.22)	(-0.51)	(1.17)
β×D		-2.66		**-3.59**		**-4.19**		**-4.50**
		(-1.64)		**(-2.89)**		**(-6.68)**		**(-9.54)**
Model	MM	MM	FFC	FFC	MM	MM	FFC	FFC
SE's	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB
T (Days)	1,138	1,138	1,138	1,138	8,041	8,041	8,041	8,041
Adj. R2	3.1%	3.3%	6.8%	6.9%	2.9%	3.1%	6.8%	7.0%
p(MKT:λ=R)	53.3%	36.3%	96.9%	61.0%	13.8%	75.2%	8.7%	67.4%

Note: Results for Fama-MacBeth regressions of daily excess returns on factor loadings for individual stocks. Returns are expressed in basis points per day. Factor loadings are computed in a first stage regression using 252 day rolling windows. We require a minimum of 126 return observations for a stock to be included. In the second stage, day t+1 excess returns are then regressed on factor loadings computed in the rolling window ending on day t. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. Fama-MacBeth estimates are estimated seperately for "Announcement Days" and "Non-Announcement Days", where "Announcement Days" are days in our sample with scheduled FOMC meetings (using only the second day for two day meetings), BLS releases of job market data and producer prices. *t*-Stats are reported in parentheses and computed using Fama-MacBeth standard errors. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the p-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Internet Appendix

Appendix A1: Construction of Test Assets

We construct 400 test assets by simultaneously sorting on eight characteristics and forecast dispersion. Test assets are sorted into characteristic deciles and dispersion quintiles, so that for each characteristic we form 50 test assets. Returns are value-value weighted according to the beginning of the month market capitalization for each stock included in a test asset. The characteristics we test are market beta, alpha, idiosyncratic volatility (ivol), size, value, investment, profitability, and momentum. Below, we explain how stocks are sorted on each anomaly characteristic.

Forecast Dispersion: We compute our dispersion variable each month by ranking stocks according to lagged values of dispersion in analysts' EPS forecasts (See Section 3, "Computing Firm-Level Dispersion"). Analyst forecasts are collected from the IBES system. To be considered current, a forecast must be posted in IBES within 105 days of the earnings announcement and posted prior to the earnings announcement. Dispersion is calculated at each earnings announcement as the standard deviation of the available analyst forecasts scaled by the absolute value of the actual EPS reported. Dispersion values are then lagged into the month following the earnings announcement and maintained in our sample until the next lagged value is available or six months have elapsed. Stocks are sorted into test assets by quintile in the dispersion measure, so that there are are five levels of variation in dispersion across test assets from low (Q1) to high (Q5) dispersion. Quintile groups are computed relative to our sample in each month.

Market Beta: We compute market beta for each stock in our sample using 60 month rolling window regressions of the market model. We require a minimum of 30 observed returns in each rolling window to compute a valid market beta and be included in market beta test assets. We lag betas into the next month following each rolling window then sort stocks into beta deciles relative to our sample each month. For each beta decile, we assign stocks to one of five test assets based on each stocks' dispersion quintile assignment. Thus, stocks are sorted into 50 tests assets where sorting is simultaneous on market betas and dispersion. For daily returns, we compute betas using 252 day rolling windows with a minimum of 126 return observations.

Alpha & Ivol: We compute alpha for each stock in our sample using 60 month rolling window regressions of the FFC model, such that alpha reflects mispricing relative to known risk factors. We compute ivol as the standard deviation of residuals from the same rolling window regression. We require a minimum of 30 observed returns in each rolling window to compute valid parameters and be included in test assets. As when constructing market beta test assets, we lag parameters into the next month then sort stocks into deciles relative to our sample each month. For each alpha or ivol decile, we assign stocks to one of five test assets based on each stocks' dispersion quintile assignment. Thus, stocks are sorted into 50 tests assets where sorting is simultaneous on alphas and dispersion or ivol and dispersion.

Size: We compute size as the market equity at the end of each month. Market equity is the shares oustanding (CRSP:SHROUT) times the share price (CRSP:PRC). We lag size into the next month then sort stocks into deciles relative to our sample each month. Since our sample is biased towards larger stocks, we sort based on our sample instead of NYSE breakpoints so that each test asset has a similar number of stocks. For each size decile, we assign stocks to one of five test assets based on each stocks' dispersion quintile assignment. Thus, stocks are sorted into 50 tests assets where sorting is simultaneous on size and dispersion.

Value: We follow Fama and French (2016) in computing value as the ratio of book equity to market equity, that is the BE/ME ratio. Book equity is computing using COMPUSTAT data based on annual filings for each firm, then lagged from the year data is reported into the next July for July to June assignment. Book equity equals stockholders equity (COMUPSTAT:SEQ or CEQ+PSTK or AT-LT) plus deferred tax assets (COMPUSTAT:TXDITC) less pension liabilities (COMPUSTAT:PRCA) less preferred stock (COMPUSTAT:PSTKRV or PSTKL or PSTK). Market equity is taken as the December value for the year in which book equity data is reported, then lagged from December to July. We sort stocks into BE-ME deciles based on the breakpoints we download for NYSE stocks from Kenneth French's website. For each BE-ME decile, we assign stocks to one of five test assets based on each stocks' dispersion quintile assignment. Thus, stocks are sorted into 50 tests assets where sorting is simultaneous on value and dispersion.

Profitability: We follow Fama and French (2016) in computing profitability as the ratio of operation profitability to book equity. Operating profitability is computed using COMPUSTAT data based on annual filings for each firm, then lagged from the year data is reported into the next July for July to June assignment. Operating profitability equals revenue (COMPUSTAT:REVT) less the costs of goods sold (COMPUSTAT:COGS), less selling, general, and administrative expenses (COMPUSTAT:XSGA), less interest expense (COMPUSTAT:XINT). Operating profitability is scaled by book equity (computed as above) then sorted into profitability deciles based on the breakpoints we download for NYSE stocks from Kenneth French's website. For each profitability decile, we assign stocks to one of five test assets based on each stocks' dispersion quintile assignment. Thus, stocks are sorted into 50 tests assets where sorting is simultaneous on profitability and dispersion.

Investment: We follow Fama and French (2016) in computing investment as the growth in total assets. Investment is computed using COMPUSTAT data based on annual filings for each firm, then lagged from the year data is reported into the next July for July to June assignment. For each year, investment is the change in total assets (COMPUSTAT:AT) from the prior year, scaled by the prior year value. We sort firms into investment deciles based on the breakpoints we download for NYSE stocks from Kenneth French's website. For each investment decile, we assign stocks to one of five test assets based on each stocks' dispersion quintile assignment. Thus, stocks are sorted into 50 tests assets where sorting is simultaneous on investment and dispersion.

Momentum: We compute momentum as the 11-1 return for each stock, where returns are cumulated for 11 months then lagged 1 month prior to decile assignment. We sort stocks into momentum deciles based on the breakpoints we download for NYSE stocks from Kenneth French's website. For each momentum decile, we assign stocks to one of five test assets based on each stocks' dispersion quintile assignment. Thus, stocks are sorted into 50 tests assets where sorting is simultaneous on momentum and dispersion.

DMA Factor: To control for the forecast dispersion anomaly (Diether et al. (2002)), we construct a "Disagreement" minus "Agreement" zero cost portfolio from our market beta by forecast dispersion test assets. For the long leg, we take the mean return each month of the 10 market beta test assets formed from high (Q5) dispersion stocks. The short leg uses the 10 test assets formed from low (Q1) dispersion stocks.

Appendix A2: Control Variables

We include the following firm-level controls in Table 7, Panel A when regressing net arbitrage trading (NAT) on market betas, $\beta \times D$, and D.

- **ln(ME):** The log of market equity, which is computed with CRSP data as shares outstanding (CRSP:SHROUT) times price per share (CRSP:PRC). We lag values one month.

- **BEME:** The ratio of book equity to market equity. Book equity is computing using COMPUSTAT data based on annual filings for each firm, then lagged from the year data is reported into the next July for July to June assignment. Book equity equals stockholders equity (COMUPSTAT:SEQ or CEQ+PSTK or AT-LT) plus deferred tax assets (COMPUSTAT:TXDITC) less pension liabilities (COMPUSTAT:PRCA) less preferred stock (COMPUSTAT:PSTKRV or PSTKL or PSTK). Market equity is taken as the December value for the year in which book equity data is reported, then lagged from December to July.

- **OP**: Operating profitability is computed using COMPUSTAT data based on annual filings for each firm, then lagged from the year data is reported into the next July for July to June assignment. Operating profitability equals revenue (COMPUSTAT:REVT) less the costs of goods sold (COMPUSTAT:COGS), less selling, general, and administrative expenses (COMPUSTAT:XSGA), less interest expense (COMPUSTAT:XINT). Operating profitability is scaled by book equity (computed as above).

- **INV**: Investment is computed using COMPUSTAT data based on annual filings for each firm, then lagged from the year data is reported into the next July for July to June assignment. For each year, investment is the change in total assets (COMPUSTAT:AT) from the prior year, scaled by the prior year value.

- **D/E**: The debt to equity ratio, computed using COMPUSTAT data as the ratio of total liabilities (COMPUSTAT:LT) to book equity (computed as above) based on annual filings for each firm. D/E is computed from the year data is reported then lagged into the next July for July to June assignment.

- **11-1 Ret**: We compute momentum as the 11-1 return for each stock, where returns are cumulated for 11 months then lagged 1 month.

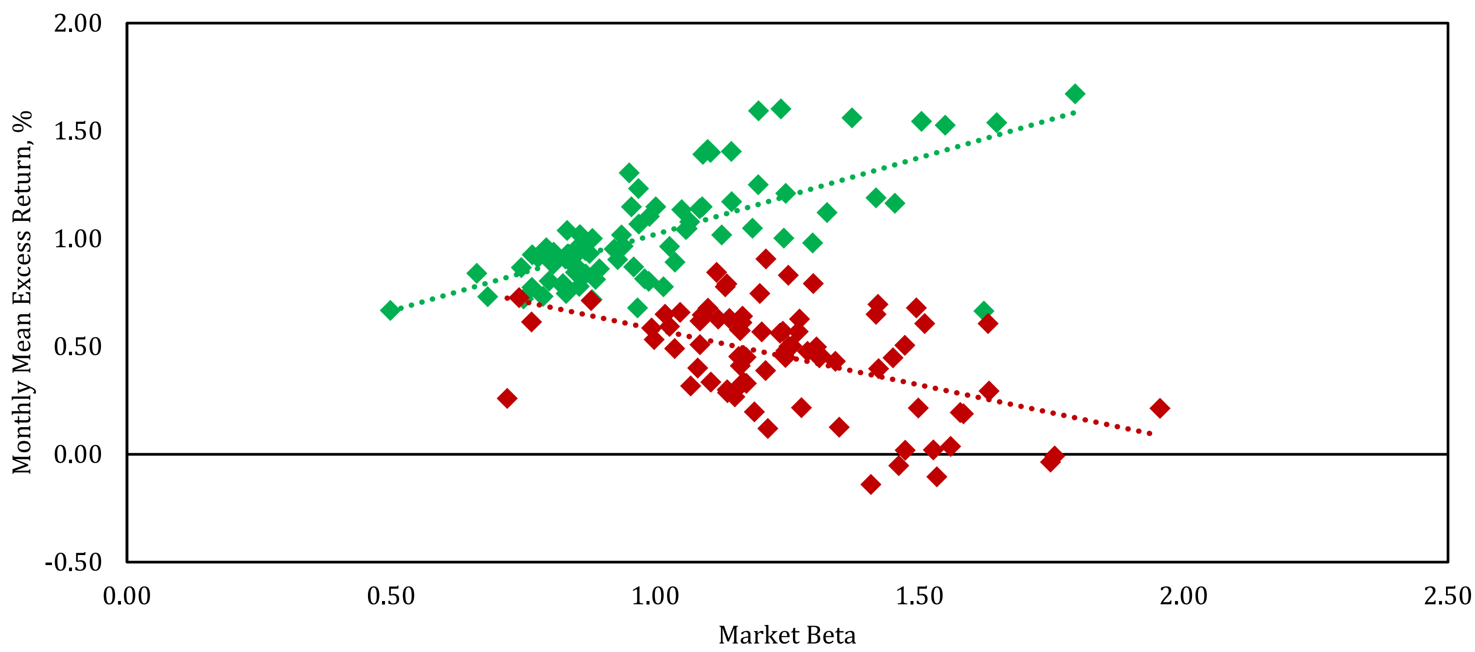
- **Div. Yield**: We compute dividend yield as the ratio dividends paid per share (COMPUSTAT:DIVRAT) to the share price (CRSP:PRC), where we lag price data from

CRSP one month and dividend data from COMPUSTAT by three months to ensure we include data that is publicly available in our tests. We set missing values to zero and include a dummy for missing values.

All values are winsorized at the 1% and 99% level.

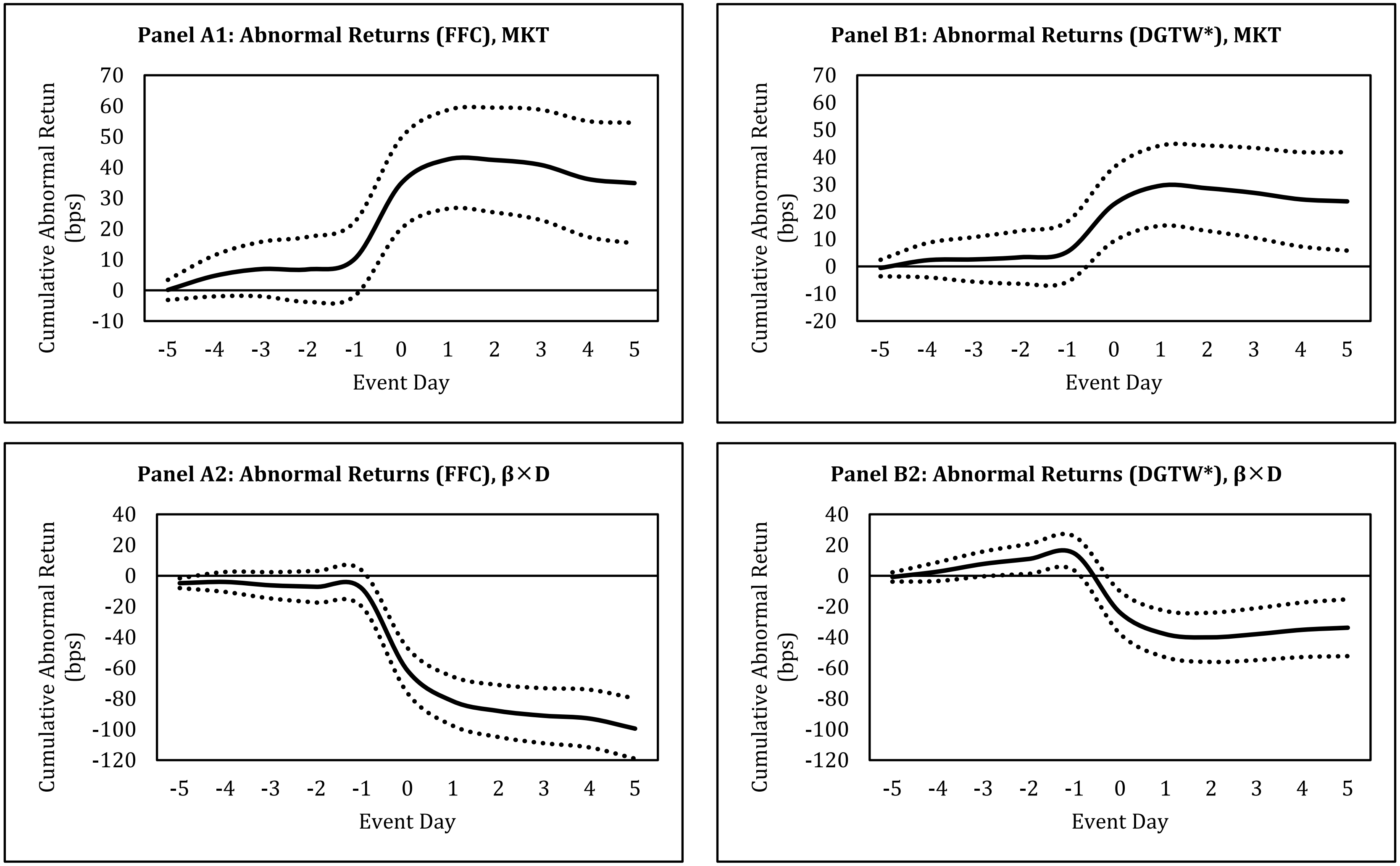
Appendix Tables & Figures

Appendix Figure 1: Anomaly Characteristics x Forecast Dispersion Test Assets



Note: Mean excess returns for twenty (ten "high" and ten "low") test assets contstructed eight anomaly characteristics (deciles) and analysts' forecast dispersion (quintiles). Q1 (green) test assets include stocks from the bottom quintile of forecast dispersion and Q5 (red) test assets from the top. Characteristics tested are market beta, alpha (computed using the Fama-French-Carhart (FFC) model), ivol (computed using the FFC model), momentum, size, value, profitability, and investment. See Appendix A1 for description of anomaly characteristic test assets. Test asset returns are value-weighted. The sample period is Aug. 1986-Dec. 2022. Dotted lines are SMLs fitted from regressions of full sample mean returns on full sample market betas, computed using monthly data.

Appendix Figure 2



Note: Cumulative abnormal returns correlated with MKT and β×D factor loadings at earnings announcements. Panel A plots abnormal returns computed with respect the the FFC. Panel B plots abnormal returns relative to our modified DGTW benchmark returns, computed by sorting on market betas, dispersion, size and value. Dotted lines represent 90%-confidence intervals.

Appendix Table 1: Pooled Regressions, Individual Stock Monthly Returns vs. Factor Loadings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**0.58**	0.30	**0.65**	0.36	**0.63**	0.37	**0.66**	0.39
	(2.85)	(1.25)	**(3.12)**	(1.51)	**(3.30)**	(1.58)	**(3.38)**	(1.64)
MKT	0.28	**0.60**	0.23	**0.55**	0.26	**0.55**	0.23	**0.52**
	(1.59)	**(3.91)**	(1.46)	**(3.90)**	(1.74)	**(4.56)**	(1.63)	**(4.44)**
β×D		**-0.50**		**-0.51**		**-0.47**		**-0.49**
		(-2.71)		**(-2.88)**		**(-2.58)**		**(-2.75)**
SMB					-0.01	0.01	0.00	0.02
					(-0.10)	(0.06)	(0.05)	(0.22)
HML					0.00	0.01	-0.02	-0.01
					(0.05)	(0.12)	(-0.24)	(-0.17)
UMD					-0.20	**-0.22**	-0.22	**-0.23**
					(-1.94)	**(-2.23)**	**(-2.27)**	**(-2.49)**
DMA			0.04	**0.08**			0.09	**0.12**
			(1.46)	**(3.90)**			(0.92)	(1.36)
SE's	Cl(Mo.)	Cl(Mo.)	Cl(Mo.)	Cl(Mo.)	Cl(Mo.)	Cl(Mo.)	Cl(Mo.)	Cl(Mo.)
T (Mos.)	437	437	437	437	437	437	437	437
Adj. R2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
p(MKT:λ=R)	16.4%	76.0%	10.2%	60.9%	11.0%	59.6%	11.0%	59.6%

Note: Results for pooled regressions of monthly excess returns on factor loadings for individual stocks. Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β× I interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. "DMA" is the analysts' forecast dispersion anomaly, tested as the factor loadings on a long-short portfolio of high vs. low dispersion stocks (Diether et al., 2002). See Appendix A1 for detail on construction of the DMA factor. *t*-Stats are reported in parentheses and computed using standard errors clustered by month. |*t* -Stats| > 2.00 are indicated in **bold.** p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Appendix Table 2: Daily Stock Returns

	(1)	(2)	(3)	(4)
Intercept	**3.54**	1.57	**3.41**	1.14
	(4.14)	(1.61)	**(5.60)**	(1.59)
MKT	1.08	**3.31**	0.53	**2.94**
	(0.82)	**(2.76)**	(0.47)	**(2.61)**
β×D		**-4.00**		**-4.39**
		(-5.35)		**(-8.75)**
SMB			-0.10	0.13
			(-0.13)	(0.17)
HML			0.43	0.51
			(0.57)	(0.68)
UMD			-1.48	-1.76
			(-1.27)	(-1.53)
SE's	NW(10)	NW(10)	NW(10)	NW(10)
T (Days)	9,179	9,179	9,179	9,179
Adj. R2	2.9%	3.1%	6.8%	6.9%
p(MKT:λ=R)	19.6%	96.3%	8.4%	78.7%

Note: Results for Fama-MacBeth regressions of daily excess returns on factor loadings for individual stocks. Returns are expressed in basis points. Factor loadings are computed in a first stage regression using 252 day rolling windows. We require a minimum of 126 return observations for a stock to be included. In the second stage, day *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending on day *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. *t*-Stats are reported in parentheses and computed using Newey-West standard errors with ten days of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Appendix Table 3: Robustness Tests

	Sample Period		Analyst Coverange		Forecast Dispersion		Size (MVE)		Estimation Window		Winzorized
	1st-Half	2nd-Half	< Median	≥ Median	< Median	≥ Median	< Median	≥ Median	24 Mos.	36 Mos.	Betas
Intercept	0.26	0.09	0.12	0.23	0.19	-0.11	0.13	0.27	0.32	0.23	0.10
	(1.07)	(0.26)	(0.52)	(1.14)	(0.98)	(-0.40)	(0.48)	(1.51)	(1.40)	(1.06)	(0.51)
MKT	**0.56**	**0.75**	**0.76**	**0.57**	**0.57**	**1.07**	**0.84**	**0.50**	**0.52**	**0.60**	**0.70**
	(2.94)	**(3.52)**	**(4.87)**	**(3.82)**	**(3.41)**	**(5.73)**	**(5.56)**	**(3.27)**	**(4.71)**	**(4.62)**	**(4.31)**
β×D	**-0.55**	**-0.76**	**-0.82**	**-0.50**	**-0.87**	**-1.08**	**-0.86**	**-0.50**	**-0.51**	**-0.58**	**-0.72**
	(-3.35)	**(-4.30)**	**(-5.97)**	**(-3.78)**	**(-5.07)**	**(-4.62)**	**(-5.91)**	**(-4.22)**	**(-4.62)**	**(-4.99)**	**(-5.32)**
Model	FFC	FFC	FFC	FFC	FFC	FFC	FFC	FFC	FFC	FFC	FFC
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	219	218	437	437	437	437	437	437	437	437	437
Adj. R2	6.6%	3.9%	4.3%	7.8%	5.5%	5.0%	3.8%	8.4%	4.4%	5.0%	5.2%
p(MKT:λ=R)	88.3%	98.5%	75.4%	68.2%	69.1%	17.0%	55.0%	50.1%	52.1%	75.3%	92.6%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for individual stocks. Fama-French-Carhart (FFC) Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. "Sample Period" splits our sample at the midpoint (Oct.-2004) and tests before (1st-Half) and after (2nd-Half) subperiods. "Analyst Coverage" splits our sample each month at the median number of analysts covering each stock in our sample. "Forecast Dispersion" splits our sample each month at the median level of forecast dispersion in the IBES sample. "Size" splits our sample each month at the median market value of equity. "Estimation Window" uses factor loadings estimated in 24 month (min. 18 obs.) and 36 month (min. 24 obs.) rolling windows. "Winzorized Betas" uses factor loadings winzorized each month at the 5% and 95% levels to mitigate the effect of outliers. *t*-Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return for each period tested.

Appendix Table 4: Stock Characteristics

Panel A: Firm Characteristics

	Unitized					Winsorized (1%-99%)				
	(U1)	(U2)	(U3)	(U4)	(U5)	(R1)	(R2)	(R3)	(R4)	(R5)
Intercept	0.47	-0.02	**0.52**	0.22	0.55	1.25	0.08	0.30	0.24	1.18
	(1.50)	(-0.09)	**(2.14)**	(0.95)	(1.62)	(1.56)	(0.42)	(1.31)	(1.11)	(1.61)
MKT	**0.62**	**0.70**	**0.67**	**0.65**	**0.69**	**0.62**	**0.66**	**0.66**	**0.64**	**0.65**
	(4.30)	**(4.74)**	**(4.42)**	**(4.15)**	**(5.53)**	**(4.30)**	**(4.43)**	**(4.41)**	**(4.11)**	**(5.05)**
β×D	**-0.67**	**-0.68**	**-0.65**	**-0.62**	**-0.72**	**-0.67**	**-0.68**	**-0.61**	**-0.61**	**-0.69**
	(-5.94)	**(-5.54)**	**(-5.18)**	**(-5.13)**	**(-6.53)**	**(-5.98)**	**(-5.74)**	**(-4.76)**	**(-4.94)**	**(-6.41)**
SIZE	-0.42				-0.44	-0.07				-0.07
	(-1.47)				(-1.58)	(-1.50)				(-1.54)
BEME		0.39			0.12		0.16			0.03
		(1.69)			(0.44)		(1.03)			(0.22)
INVT			**-0.63**		**-0.51**			**-0.58**		**-0.48**
			(-4.53)		**(-4.51)**			**(-4.92)**		**(-4.80)**
PROF				-0.01	0.14				-0.03	0.09
				(-0.04)	(0.60)				(-0.23)	(0.64)
Model	MM	MM	MM	MM	MM	MM	MM	MM	MM	MM
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	437	437	437	437	437
Adj. R2	4.1%	3.8%	3.4%	3.6%	5.5%	4.1%	3.8%	3.4%	3.6%	5.4%
p(MKT:λ=R)	83.6%	93.6%	97.6%	92.2%	97.6%	83.1%	95.4%	95.4%	89.7%	91.3%

Note: Results for Fama-MacBeth regressions of monthly excess returns on characteristics for individual stocks. Market betas are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on firm characteristics available in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. "Unitized" results regress excess returns on characteristics mapped to a [0,1] ranking each month. "Winsorized" results regress excess returns on characteristics winsorized at the 1% and 99% levels each month. See Appendix A2 for a description of stock characteristics. *t*-Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market return.

Panel A: "SIZE" is the log of market capitalization. Following Fama and French (2015), "BEME" is the book-to-market value of equity, "INVT" is the change in total assets, and "PROF" is operating profitability.

Appendix Table 4: Stock Characteristics

Panel B: Risk Measures

	Unitized					Winsorized (1%-99%)				
	(U1)	(U2)	(U3)	(U4)	(U5)	(R1)	(R2)	(R3)	(R4)	(R5)
Intercept	0.18	0.30	0.31	0.14	0.26	0.12	0.24	0.32	0.24	0.16
	(0.79)	(1.17)	(1.47)	(0.70)	(1.20)	(0.45)	(1.06)	(1.60)	(1.09)	(0.68)
MKT	**0.56**	**0.63**	**0.62**	**0.63**	**0.57**	**0.56**	**0.63**	**0.64**	**0.63**	**0.56**
	(4.32)	**(4.10)**	**(4.43)**	**(4.30)**	**(5.08)**	**(4.26)**	**(4.10)**	**(4.73)**	**(3.98)**	**(5.14)**
$\beta \times D$	**-0.63**	**-0.63**	**-0.62**	**-0.65**	**-0.66**	**-0.67**	**-0.63**	**-0.62**	**-0.62**	**-0.68**
	(-6.43)	**(-5.06)**	**(-4.84)**	**(-5.55)**	**(-6.75)**	**(-7.11)**	**(-5.12)**	**(-4.88)**	**(-4.99)**	**(-7.43)**
IVOL	0.33				0.31	0.03				0.08
	(0.89)				(0.84)	(0.40)				(0.92)
COSKEW		-0.11			-0.07		-0.01			-0.01
		(-0.76)			(-0.54)		(-1.37)			(-0.78)
DRISK			-0.14		-0.16			-0.10		-0.14
			(-0.63)		(-0.74)			(-0.79)		(-0.89)
ILLQ				0.22	0.07				-0.07	0.22
				(0.90)	(0.32)				(-0.10)	(0.41)
Model	MM	MM	MM	MM	MM	MM	MM	MM	MM	MM
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	437	437	437	437	437
Adj. R2	4.5%	3.4%	3.7%	4.0%	5.7%	4.8%	3.5%	3.8%	3.6%	6.0%
p(MKT:λ=R)	63.7%	86.6%	83.8%	85.6%	66.9%	63.0%	86.0%	89.5%	84.8%	62.9%

Panel B: "IVOL" is idiosyncratic volatility relative to the Fama-French-Carhart (FFC) model. "COSKEW" is coskewness with the market return as in Harvey and Siddique (2000). "DRISK" is downside beta, which is the beta on the market return when the market return is below average, as in Bawa and Lindenberg (1977). IVOL, COSKEW, and DRISK are computed on the prior year of daily returns ending in month t. "ILLQ" is the month t average of absolute stock return relative to the daily dollar trading volume as in Amihud (2002). We require a minimum of 15 daily returns to compute ILLQ.

Appendix Table 4: Stock Characteristics

Panel C: Lottery Demand

	Unitized					Winsorized (1%-99%)				
	(U1)	(U2)	(U3)	(U4)	(U5)	(R1)	(R2)	(R3)	(R4)	(R5)
Intercept	0.23	0.12	0.42	0.39	0.61	0.19	0.23	0.44	0.43	**0.74**
	(0.71)	(0.51)	(1.95)	(1.44)	(1.73)	(0.87)	(1.01)	(1.97)	(1.47)	**(2.98)**
MKT	**0.50**	**0.62**	**0.66**	**0.65**	**0.62**	**0.51**	**0.63**	**0.66**	**0.66**	**0.61**
	(3.58)	**(4.00)**	**(4.82)**	**(4.31)**	**(5.05)**	**(3.60)**	**(4.02)**	**(4.71)**	**(4.40)**	**(4.92)**
$\beta \times D$	**-0.57**	**-0.63**	**-0.57**	**-0.64**	**-0.58**	**-0.57**	**-0.63**	**-0.57**	**-0.64**	**-0.56**
	(-4.98)	**(-5.06)**	**(-5.05)**	**(-5.64)**	**(-6.03)**	**(-4.89)**	**(-4.98)**	**(-5.18)**	**(-5.63)**	**(-5.86)**
MOME	0.31				0.33	0.24				0.24
	(0.94)				(1.00)	(0.93)				(0.94)
SKEW		**0.27**			0.11		**0.07**			0.03
		(2.14)			(0.97)		**(2.01)**			(0.91)
MAX			-0.42		**-0.64**			**-0.10**		**-0.11**
			(-1.63)		**(-3.10)**			**(-2.49)**		**(-3.32)**
SPEC				-0.32	**-0.49**				-0.78	**-1.02**
				(-1.31)	**(-2.29)**				(-1.72)	**(-2.47)**
Model	MM	MM	MM	MM	MM	MM	MM	MM	MM	MM
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	437	437	437	437	437
Adj. R2	4.2%	3.3%	4.0%	3.9%	5.7%	4.2%	3.3%	4.2%	3.9%	5.9%
p(MKT:λ=R)	50.4%	84.0%	94.5%	91.4%	80.4%	51.4%	84.5%	94.3%	94.1%	79.4%

Panel C: "MOME" is 11-1 raw return. "SKEW" is the unadjusted skewness of returns, measured over the prior year of daily returns. "MAX" is lottery returns as in Bali et al. (2017), defined as the average of the five highest returns observed in month t. We require a minimum of 15 daily returns to compute MAX. "SPEC" is speculative beta as in Hong and Sraer (2016), defined as the ratio of a stock's market beta to idiosyncratic volatility. We compute market model betas and idiosyncratic volatility on the prior year of daily returns for SPEC.

Appendix Table A5: Alternative Risk Factors

	(1)	(2)	(3)	(4)	(5)
Intercept	0.19	0.24	0.17	0.16	0.22
	(0.79)	(1.06)	(0.82)	(0.77)	(1.06)
MKT	**0.66**	**0.60**	**0.65**	**0.66**	**0.60**
	(4.04)	**(3.64)**	**(4.43)**	**(4.62)**	**(4.29)**
β×D	**-0.65**	**-0.57**	**-0.67**	**-0.66**	**-0.60**
	(-5.20)	**(-5.30)**	**(-5.81)**	**(-5.89)**	**(-5.18)**
VIX	**-0.66**				
	(-2.01)				
VIX Δ		-0.21			
		(-1.68)			
EUNC			-0.66		
			(-1.71)		
BAB				0.10	
				(0.90)	
FMAX					0.08
					(0.46)
Model	FFC	FFC	FFC	FFC	FFC
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	365	365	437	437	437
Adj. R2	5.2%	4.9%	5.5%	5.5%	5.6%
p(MKT:λ=R)	92.4%	75.5%	92.9%	93.0%	77.5%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for individual stocks. Fama-French-Carhart (FFC) Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. In addition to FFC factors, we control for alternative risk factors in the first stage regression and test loadings on each alternative in the second stage. "VIX" and "VIX Δ" test the beginning of month level and concurrent shock of the S&P 500 VIX index from the CBOE. "EUNC" is the macroeconomic uncertainty index from Jurado et al. (2015) and Bali et al. (2017A). "BAB" is the betting-against-beta factor from Frazzini and Pedersen (2014). "FMAX" is the lottery return factor from Bali et al. (2017B). *t*-Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return for each period tested.

Appendix Table A6: Short Sale Constraints, Fama-MacBeth Regressions

	TED Spread		Short Interest	
	< Median	≥ Median	< Median	≥ Median
Intercept	0.03	-0.29	-0.39	0.19
	(0.11)	(-0.94)	(-1.62)	(0.86)
MKT	**0.41**	**0.88**	**0.63**	**0.55**
	(2.75)	**(4.18)**	**(4.31)**	**(3.68)**
β×D	**-0.56**	**-0.72**	**-0.65**	**-0.48**
	(-3.41)	**(-3.96)**	**(-4.37)**	**(-3.50)**
D	**-0.60**	**-1.10**	**-0.89**	**-0.96**
	(-2.21)	**(-3.44)**	**(-2.84)**	**(-3.53)**
σ(D)	**2.78**	1.30	**2.57**	0.48
	(4.48)	(1.67)	**(3.87)**	(0.82)
Model	FFC	FFC	FFC	FFC
SE's	FMB	FMB	NW(6)	NW(6)
T (Mos.)	215	211	437	437
Adj. R2	4.9%	6.1%	5.9%	5.8%
p(MKT:λ=R)	28.9%	67.8%	86.0%	61.5%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for individual stocks. Fama-French-Carhart (FFC) Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. D and σ(D) are the level and volatility (in the first stage rolling window) of our forecast dispersion measure. To reduce collinearity, we cross-sectionally residualize D each month on β and β×D prior to the second stage regression. "TED Spread" seperates our sample based on the beginning of the month level of the TED Spread (3 mo. LIBOR minus 3 mo. T-Bill rates, downloaded from https://fred.stlouisfed.org/series/TEDRATE). High TED spreads proxy for high short-selling costs. "Short Interest" seperates our sample each month based on the stock-level of shares sold short relative to shares outstanding from the COMPUSTAT monthly short interest file. Short sale data is lagged one month. *t*-Stats are reported in parentheses and computed using Fama-MacBeth (FMB) or Newey-West (NW) standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Appendix Table 7: Short Sale Constraints, Pooled Regressions			
	(1)	(2)	(3)
Intercept	-0.20	-0.13	-0.20
	(-0.60)	(-0.42)	(-0.55)
MKT	**0.54**	**0.51**	**0.52**
	(4.60)	**(3.83)**	**(3.97)**
β×D	**-0.48**	**-0.40**	**-0.43**
	(-2.45)	**(-2.41)**	**(-2.32)**
D	**-1.05**	**-0.90**	**-1.05**
	(-4.23)	**(-3.67)**	**(-4.02)**
σ(D)	**3.06**	**2.88**	**2.79**
	(-4.23)	**(2.57)**	**(2.30)**
TED Spread	**-0.41**		-0.40
	(4.60)		(-0.66)
×β×D	-0.03		-0.03
	(-0.11)		(-0.10)
×D	-0.64		**-0.75**
	(-1.91)		**(-2.22)**
×σ(D)	-1.72		**-2.52**
	(-1.47)		**(-2.09)**
Short Interest		**0.62**	**0.55**
		(6.07)	**(5.34)**
×β×D		-0.03	-0.05
		(-0.33)	(-0.60)
×D		**0.12**	0.09
		(-6.09)	(0.63)
×σ(D)		**-3.20**	**-2.71**
		(-6.09)	**(-5.31)**
Model	FFC	FFC	FFC
SE's	Cl(Mo.)	Cl(Mo.)	Cl(Mo.)
T (Mos.)	426	437	426
Adj. R2	0.3%	0.1%	0.4%
p(MKT:λ=R)	57.9%	50.0%	53.6%

Note: Results for pooled regressions of monthly excess returns on factor loadings for individual stocks. Fama-French-Carhart (FFC) Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. D and σ(D) are the level and volatility (in the first stage rolling window) of our forecast dispersion measure. To reduce collinearity, we cross-sectionally residualize D each month on β and β×D prior to the second stage regression. "TED Spread" seperates our sample based on the beginning of the month level of the TED Spread (3 mo. LIBOR minus 3 mo. T-Bill rates, downloaded from https://fred.stlouisfed.org/series/TEDRATE). High TED spreads proxy for high short-selling costs. "Short Interest" seperates our sample each month based on the stock-level of shares sold short relative to shares outstanding from the COMPUSTAT monthly short interest file. Short sale data is lagged one month. *t*-Stats are reported in parentheses and computed using Fama-MacBeth (FMB) or Newey-West (NW) standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold** Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Appendix Table 8: Event Windows around Earnings Announcement Dates, Modified DGTW

Event Day	w/i Dispersion		Benchmarked		
	Q1	Q5	Intercept	MKT	β×D
-5	1.69	1.81	1.23	-0.59	-0.79
	(1.84)	(1.14)	(0.67)	(-0.32)	(-0.43)
-4	0.32	**6.12**	-1.81	2.87	3.51
	(0.19)	**(2.19)**	(-0.52)	(0.86)	(1.08)
-3	0.96	**7.72**	1.54	0.29	5.01
	(0.61)	**(2.77)**	(0.48)	(0.09)	(1.56)
-2	3.09	**9.90**	1.51	0.79	3.25
	(1.96)	**(3.56)**	(0.47)	(0.25)	(1.01)
-1	**6.40**	**11.92**	5.37	1.98	3.53
	(3.90)	**(4.18)**	(1.64)	(0.62)	(1.06)
0	**14.91**	**-28.48**	**-11.96**	**17.40**	**-38.49**
	(5.46)	**(-6.84)**	**(-2.55)**	**(3.71)**	**(-7.69)**
1	**5.69**	**-6.89**	-4.64	6.84	**-14.01**
	(3.12)	**(-2.22)**	(-1.30)	(1.94)	**(-3.85)**
2	-0.35	-4.83	0.37	-0.95	-2.05
	(-0.22)	(-1.69)	(0.12)	(-0.30)	(-0.63)
3	-0.08	1.13	2.25	-1.68	2.07
	(-0.05)	(0.40)	(0.70)	(-0.53)	(0.63)
4	-0.91	1.59	4.10	-2.38	2.81
	(-0.58)	(0.56)	(1.24)	(-0.75)	(0.87)
5	1.29	4.38	3.65	-0.75	1.37
	(0.84)	(1.58)	(1.15)	(-0.24)	(0.43)
[-5,5]	**33.01**	4.36	1.62	**23.81**	**-33.80**
	(5.85)	(0.45)	(0.15)	**(2.18)**	**(-3.01)**
Model	DGTW*	DGTW*		DGTW*	
SE's	Cl(Event)	Cl(Event)		Cl(Event)	
Events	63,781	50,975		291,810	

Note: Results for event studies of abnormal returns for individual stocks in the [-5,5] event window around earnings announcement dates. Returns are expresses in basis points. Abnormal returns are computed with respect to our modified DGTW benchmark portfolios. Following Daniel et al. (1997), we form portfolios based on market beta (quintiles), dispersion (quintiles), size (3-4-3 deciles), and book-to-market value (3-4-3 deciles). The β×D interaction is found by multiplying the stock-level market beta and analysts' forecast dispersion, where forecast dispersion is computed using data on each firms's prior earnings announcement. We cross-sectionally demean the interaction each month prior to the second stage regression. *t*-Stats are reported in parentheses and computed using standard errors clustered by events. |t-Stats| > 2.00 are indicated in **bold.**

Appendix Table 9: Fama-MacBeth Regressions, 400 Test Assets vs. Factor Loadings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**0.66**	0.04	0.43	0.08	**0.77**	0.12	**0.59**	0.13
	(2.68)	(0.14)	(1.71)	(0.29)	**(5.11)**	(0.59)	**(3.76)**	(0.72)
MKT	0.06	0.59	0.31	0.58	-0.05	**0.52**	0.13	**0.51**
	(0.19)	(1.90)	(1.01)	(1.84)	(-0.24)	**(2.76)**	(0.68)	**(2.72)**
β×D		**-0.73**		**-0.65**		**-0.68**		**-0.67**
		(-5.07)		**(-5.36)**		**(-5.28)**		**(-5.40)**
SMB					0.05	0.11	0.09	0.11
					(0.36)	(0.90)	(0.74)	(0.85)
HML					-0.19	0.02	-0.12	0.01
					(-1.20)	(0.10)	(-0.81)	(0.07)
UMD					0.17	0.00	0.10	0.02
					(0.90)	(0.01)	(0.56)	(0.09)
DMA			**-0.40**	0.01			**-0.45**	0.02
			(-2.61)	(0.07)			**(-3.03)**	(0.14)
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	437	437	437
Adj. R2	10.9%	15.2%	15.4%	17.2%	20.0%	22.6%	21.7%	23.1%
p(MKT:λ=R)	10.8%	82.2%	33.4%	78.7%	1.8%	58.3%	6.0%	56.3%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for 400 test assets. There are 50 test assets formed on each of eight stock-level characteristics and returns are value weighted. Characteristics tested are market beta, alpha (computed using the Fama-French-Carhart (FFC) model), ivol (computed using the FFC model), momentum, size, value, profitability, and investment. Momentum, value, profitability, and investment test assets are formed on the NYSE breakpoints available on Kenneth French's website. Otherwise, we sort into characteristic deciles based on our sample. For size, we sort based on our sample due to the relatively low number of small stocks with valid analysts' forecast data. See Appendix A1 for a description of test asset construction. Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β×D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. "DMA" is the analysts' forecast dispersion anomaly, tested as the factor loadings on a long-short portfolio of high vs. low dispersion stocks (Diether et al., 2002). See Appendix A1 for detail on construction of the DMA factor. *t*-Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Appendix Table 10: Price of Market Risk in Factor Models, 400 Test Assets

	Market Model	FF Three-Factors + Momentum	FF Three-Factors + Momentum + Liquidity	FF Five Factors	Q Factors	Mispricing Factors
Panel A: w/o β × D Interaction						
Intercept	**0.66**	**0.77**	**0.78**	**0.72**	**0.69**	**0.78**
	(2.68)	**(5.11)**	**(5.29)**	**(4.52)**	**(4.00)**	**(4.35)**
MKT	0.06	-0.05	-0.06	-0.00	0.03	-0.08
	(0.19)	(-0.24)	(-0.29)	(-0.01)	(0.15)	(-0.36)
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	365
Adj. R2	10.9%	20.0%	20.7%	19.8%	19.4%	19.4%
p(MKT:λ=R)	10.8%	1.8%	1.5%	3.1%	4.0%	2.9%
Panel B: w/ β × D Interaction						
Intercept	0.04	0.12	0.13	0.08	0.15	0.24
	(0.14)	(0.59)	(0.66)	(0.35)	(0.67)	(1.02)
MKT	0.59	**0.52**	**0.50**	**0.56**	**0.52**	0.40
	(1.90)	**(2.76)**	**(2.71)**	**(2.59)**	**(2.31)**	(1.78)
β×D	**-0.73**	**-0.68**	**-0.71**	**-0.71**	**-0.67**	**-0.67**
	(-5.07)	**(-5.28)**	**(-5.43)**	**(-5.15)**	**(-4.60)**	**(-4.35)**
SE's	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)	NW(6)
T (Mos.)	437	437	437	437	437	365
Adj. R2	15.2%	22.6%	23.0%	22.1%	21.8%	22.1%
p(MKT:λ=R)	82.2%	58.3%	54.4%	71.4%	60.2%	47.3%

Note: Results for Fama-MacBeth regressions of monthly excess returns on factor loadings for 400 test assets. There are 50 test assets formed on each of eight stock-level characteristics and returns are value weighted. Characteristics tested are market beta, alpha (computed using the Fama-French-Carhart (FFC) model), ivol (computed using the FFC model), momentum, size, value, profitability, and investment. Momentum, value, profitability, and investment test assets are formed on the NYSE breakpoints available on Kenneth French's website. Otherwise, we sort into characteristic deciles based on our sample. For size, we sort based on our sample due to the relatively low number of small stocks with valid analysts' forecast data. See Appendix A1 for a description of test asset construction. Factor loadings are computed in a first stage regression using 60 month rolling windows. We require a minimum of 30 return observations for a stock to be included. We compute loadings seperately for various common factor models. In the second stage, month *t+1* excess returns are then regressed on factor loadings computed in the rolling window ending in month *t*. The β× D interaction is found by multiplying the stock-level market beta and our analysts' forecast dispersion measure. We cross-sectionally demean the interaction each month prior to the second stage regression. *t* Stats are reported in parentheses and computed using Newey-West standard errors with six-months of lags. |*t*-Stats| > 2.00 are indicated in **bold**. Adjusted R2 values are computed using the Fama-MacBeth procedure. p(MKT:λ=R) is the *p*-value for the hypothesis test that the Fama-MacBeth price of market risk equals the in-sample mean market excess return.

Appendix Table 11: Mean Excess Returns by Dispersion Quintiles

	Daily Returns		Earnings Event Day		Monthly Returns		Log Annual Returns	
	Q1	Q5	Q1	Q5	Q1	Q5	Q1	Q5
Mean	0.06	0.02	0.23	-0.35	1.13	0.18	3.36	-19.52
Std. Dev.	2.91	4.65	6.70	9.29	12.93	20.45	46.08	79.21
Skew	5.65	7.51	0.08	5.48	8.44	5.01	-2.15	-1.46
Percentile								
99%	8.29	13.33	19.03	24.62	36.00	62.37	100.85	138.03
95%	4.04	6.21	10.37	12.78	19.02	29.35	60.00	81.85
90%	2.68	4.00	7.03	8.26	13.36	19.33	46.13	56.45
75%	1.15	1.58	2.96	3.12	6.55	8.05	27.77	25.39
50%	-0.02	-0.02	0.09	-0.06	0.88	-0.49	8.69	-5.52
25%	-1.09	-1.75	-2.34	-3.78	-4.72	-9.29	-14.02	-50.90
10%	-2.57	-4.02	-6.21	-9.14	-11.28	-19.88	-43.27	-115.60
5%	-3.83	-5.91	-9.91	-13.95	-16.68	-27.99	-72.16	-167.47
1%	-7.59	-11.47	-20.43	-26.59	-31.33	-47.47	-152.14	-289.62
Obs.	4,718,544	4,224,478	67,582	56,985	247,483	247,567	18,060	15,717

Note: Mean excess returns for stocks classified as low (Q1) and high (Q5) in forecast dispersion. "Daily Returns" are returns averaged for each day in our sample. "Earnings Event Days" are returns averaged on earnings announcment days, where the classification of each stock is based on results from the prior earnings announcment. "Monthly Returns" are returns for each month in out sample. "Log Annual Returns" are calendar year annualized log returns, where the classification of each stock is based on data available in the last month of the prior year and a minimum of eight returns are required for inclusion.