Asymmetries of Stock Returns and Price Delay

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Abstract

Prior studies have demonstrated that stock returns exhibit non-linear dependence – downside beta different from upside beta – and asymmetric correlations – higher correlations during periods of negative market moves than positive market moves. We provide empirical evidence that these asymmetries are intertwined with delayed pricing of negative and positive news. We demonstrate that negative news are incorporated in stock prices faster than positive news, and that idiosyncratic news are more likely to be priced during periods when systematic news are positive. Our results add to the growing evidence that investors have finite attention budgets to process information. They also imply that investors prioritize negative over positive news – an effect not yet fully explained by theory.

Keywords: Asymmetric dependence; Price delay; Inattention; Systematic factors; Downside risk; Asymmetric correlations

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1 Introduction

In a perfectly rational market without frictions in an economy subject to simultaneous shocks, asset prices instantaneously reflect all the shocks to the degree the shocks affect the assets' future payoffs and, ultimately, the investors' utility. This immediate and accurate pricing happens independently of the nature of the shock. The reality is messier: the markets are subject to frictions and information-processing limits, and shocks may take up to several months to become fully priced in (for example, stock-level liquidity shocks, as in Bali, Peng, Shen, and Tang, 2014). Investors with limited attention have to prioritize their responses to some shocks over others, resulting in faster processing of a subset of shocks judged as high-priority by the investors (e.g. Peng and Xiong, 2006; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016).

In this paper, we report evidence that negative news are priced in faster, implying that investors pay more attention to negative news.[1] We consider two types of news – systematic news, reflected in the moves of the market index, and idiosyncratic news, reflected in individual stock returns net of moves attributed to systematic news. Using price delay metrics of Hou and Moskowitz (2005), generalized to handle asymmetric price delays, we demonstrate that negative systematic news are priced in faster than positive systematic news. We show that delay in systematic news increases during periods when idiosyncratic news rise in prominence. We also demonstrate that investors pay more attention to idiosyncratic news on days when systematic news are positive, resulting in a conditional heteroscedasticity of idiosyncratic volatility – an asymmetry between idiosyncratic volatility measured on positive and negative market days. All of these empirical findings point to a dynamic of a market where investors have limited attention, and allocate this attention preferentially to negative news.

Our study connects two rich and previously largely disjointed strands of literature – those on price delay (mentioned above and discussed in greater detail below) and on asymmetric dependence of stock returns. Stock returns depend on market returns asymmetrically[2]: Harvey and Siddique

[1] Investors may pay more attention to negative news because of behavioral or structural reasons, for example borrowing constraints as in Yuan (2005).

[2] More generally, stock returns depend on underlying factors asymmetrically, which manifests in an asymmetric dependence on market returns.

(2000) demonstrated that a non-linear correction to the market model can arise when the utility function has a positive third derivative and demonstrated the importance of this non-linear correction in explaining the cross-section of stock returns. The correction for the vast majority of the smaller stocks is concave, which means that the dependence of individual stock returns on market returns for these stocks is higher when returns are negative than when they are positive. This non-linearity also manifests itself in the difference between downside and upside beta – CAPM beta estimated on negative vs. positive market days (Bawa and Lindenberg, 1977; Ang, Chen, and Xing, 2006). For most stocks, downside beta is greater than upside beta.

The dependence of stock returns on market returns exhibits not only non-linearity but also asymmetric correlations (Longin and Solnik, 2001; Ang and Chen, 2002; Hong et al., 2006; Alcock and Hatherley, 2016; Jiang et al., 2018). Stock returns are more highly correlated on negative market days than on positive market days. Asymmetric correlations are a result of conditional heteroscedasticity of idiosyncratic volatility: Idiosyncratic volatility is higher on positive days than on negative days resulting in asymmetric conditional correlations.

We show that non-linearity, which we will also call *beta asymmetry*, is higher when pricing of systematic news is delayed. Measures of non-linearity exhibit a strong and highly statistically significant dependence on the delay in pricing of systematic news. We demonstrate this dependence using portfolio sorts and cross-sectional Fama-MacBeth regressions (Black, Jensen, and Scholes, 1972; Fama and MacBeth, 1973). We show that both systematic price delay and beta asymmetry are greater during periods when idiosyncratic news are more prominent: when the ratio of idiosyncratic to total volatility is higher, when turnover is higher than in preceding years, or during periods of high kurtosis. When some of investors' attention is pulled toward idiosyncratic news, less attention is allocated toward systematic news. Systematic delay rises, particularly for positive systematic news.

When idiosyncratic news are important enough that investors allocate a significant share of their attention to them, these news get incorporated in stock prices independently of whether they coincide with positive or negative systematic news. Therefore, we would expect a negative relationship between idiosyncratic asymmetry and indicators of relative importance of idiosyncratic news.

Fama-MacBeth regressions and portfolio sorts support this hypothesis. We find that idiosyncratic asymmetry has a strong negative relationship with the ratio of idiosyncratic to total volatility, excess turnover, and kurtosis. We also would expect idiosyncratic asymmetry to rise when systematic news rise in importance, and therefore have a negative relationship with delay and a positive relationship with such measures of investor attention to systematic news as VIX and the aggregate book-to-market ratio. We find a strong negative relationship with price delay and a weak, but also positive, relationship with the book-to-market ratio and the VIX.

Our results enrich the understanding of the origins of asymmetric dependence of stock returns, which has been previously attributed to static effects such a utility with a positive third derivative (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000) or a kink associated with disappointment aversion (Gul, 1991; Ang et al., 2006). We demonstrate that dynamic information-processing effects play an important role in creating the observed asymmetric dependence.

Our results are generally in line with, but cannot be fully explained by existing theories supporting systematic price delay and differences in processing positive and negative information. For example, Hong et al. (2000) demonstrates that information diffuses gradually in the stock markets. Peng and Xiong (2006) demonstrate that investors with limited attention allocate their attention macroeconomic and sector news before they pay attention to idiosyncratic news. Kacperczyk et al. (2016) demonstrate within a rational expectations framework that investors balance their attention between news that affect the largest portfolio weight and those, where they can gain the most information not revealed by the price (see also Cziraki, Mondria, and Wu, 2019). These theories demonstrate that, all else equal, investors prioritize systematic news over idiosyncratic news; however, they do not address why investors treat positive and negative systematic news unevenly.

Differential treatment of positive and negative news has been considered in two general contexts: investor learning about an unknown "good" or "bad" state of economy (David, 1997; Veronesi, 1999; Conrad et al., 2002; Guidolin and Timmermann, 2007; Loh and Stulz, 2018) and ambiguity aversion (Epstein and Schneider, 2008; Ju and Miao, 2012). In the two-state model with regime switching, bad news deliver more information to investors in "good times" and investors react more strongly to bad news than to good news during these times; however, during "bad times", investors react more strongly to good news, creating, over a long period of time, a symmetric effect between positive and negative news. By contrast, the ambiguity aversion framework not only allows for an asymmetric treatment of positive and negative news, such asymmetry is built into the framework: Ambiguity-averse investors treat negative news as more certain and positive news as less certain (in line with decision-science experiments). However, this would imply that investors would prioritize learning about positive rather than negative news. Such behavior would contradict our finding about idiosyncratic pricing taking place to a greater extent on days with positive market news. Other related theories are those used to explain the momentum factor, for example De Long et al. (1990); Daniel et al. (1998); Barberis et al. (1998), which, again, explain the phenomenology we find in our study only partially.

Our results also add to the debate regarding whether "bad news" are priced in more slowly, for example, when short-selling is restricted (Hong et al., 2006; Boehmer and Wu, 2013). We find that "bad news" travel faster and, in the process, distract investors from other news. In light of our results, we interpret empirical results, such as Hong et al. (2006) and Boehmer and Wu (2013), and theoretical works, such as Diamond and Verrecchia (1987), as to imply that "bad news" travel even faster with short-selling is less restricted.[3]

We consider the possibility that the connection between measured asymmetries and price delay could arise from microstructure effects. To reduce the impact of these effects, we use weekly return data. The effect we report happen on the scale of weeks. Additionally, as a robustness check, we examine the correlation of beta and asymmetric correlations with Amihud (2002) illiquidity and find this connection to be very weak.

To summarize, we make three main contributions: First, we provide an empirical demonstration that investors treat positive and negative news asymmetrically: we demonstrate that negative systematic news are priced in faster than positive news and we show that this asymmetry increases when idiosyncratic news attract investor attention. Second, we link asymmetric dependence of stock returns – both the non-linearity and asymmetric correlations – to systematic price delay and

[3]Additional literature to consider: Volatility and risk premia both increase with attention and uncertainty – a theoretical study Andrei and Hasler (2015); Impact of private info on prices, liquidity, and volatility Kacperczyk and Pagnotta (2019); borrowing constraints Yuan (2005).

asymmetric pricing of news, thereby shedding additional light on the origin of asymmetries. Third, we propose a hypothesis to explain the empirical facts we establish: that investors with limited attention prioritize negative news over positive news. [corporate finance implications go here...]

The paper is organized as follows: Section 2 describes the study setup: definition of metrics used in the study, data description, and a statistical summary of estimated metrics. Section 3 summarizes the empirical results. Section 4 provides a discussion of corporate finance implicaionts, and Section 5 concludes.

2 Study Setup

In this section, we provide definitions for the key metrics used in this study, a description of the data, and a statistical summary of metric estimates.

2.1 Measures of Asymmetric Dependence and Price Delay

Prior literature has demonstrated that the dependence of individual stock returns on market returns is non-linear and that the correlations between individual stock returns and market returns are asymmetric (which implies that idiosyncratic risk is higher during positive market moves than negative market moves). We investigate the dependence of measures of non-linear dependence and heteroscedasticity on systematic price delay.

As the key measure of non-linearity or *beta asymmetry*, we use the difference between CAPM betas estimated during periods of positive and negative market moves, normalized by the average of the upside and downside beta. Following Ang et al. (2006), we define downside and upside betas for asset i:

$$\beta_i^- \equiv \frac{\mathrm{Cov}(r_i, r_M | r_M < \mu_M)}{\mathrm{Var}(r_M | r_M < \mu_M)} \tag{1}$$

$$\beta_i^+ \equiv \frac{\mathrm{Cov}(r_i, r_M | r_M > \mu_M)}{\mathrm{Var}(r_M | r_M > \mu_M)}, \tag{2}$$

where r_i and r_M are individual and market excess returns, and μ_M is the mean excess market return over the estimation period. Because β^+ and β^- are correlated with each other and with CAPM beta, we normalize the difference between β^+ and β^- by the average of β^+ and β^-, $\bar{\beta} \equiv (\beta^+ + \beta^-)/2$.[4] We measure nonlinear dependence using the metric:

$$\Delta^{\pm}\beta/\beta_i \equiv \frac{\beta_i^- - \beta_i^+}{\bar{\beta}_i}. \tag{3}$$

As an alternative metric of non-linearity in robustness checks we use coskewness (Harvey and Siddique, 2000), defined as $\text{Coskew}_i = E[\epsilon_i(r_M - \mu_M)^2)]/[\sqrt{\text{var}(\epsilon_i)}\text{var}(r_M)]$, estimated based on idiosyncratic stock returns $\epsilon_i = r_i - \alpha_i - \beta_i r_M$.

To measure heteroscedasticity of idiosyncratic volatility or *idiosyncratic asymmetry*, we use the difference in conditional idiosyncratic risk, normalized by unconditional idiosyncratic risk. We define:

$$\text{Idio}_i^- \equiv \text{Var}(r_i|r_M < \mu_M) - (\beta_i^-)^2\text{Var}(r_M|r_M < \mu_M) \tag{4}$$

$$\text{Idio}_i^+ \equiv \text{Var}(r_i|r_M > \mu_M) - (\beta_i^+)^2\text{Var}(r_M|r_M > \mu_M) \tag{5}$$

$$\text{Idio}_i \equiv \text{Var}(r_i) - \beta_i^2\text{Var}(r_M), \tag{6}$$

and measure heteroscedasticity using the metric:

$$\Delta^{\pm}\text{Idio}/\text{Idio} = \frac{\text{Idio}_i^+ - \text{Idio}_i^-}{\text{Idio}_i}. \tag{7}$$

For robustness checks, we use alternative measures of conditional idiosyncratic risk, such as $\text{Idio}_i^+ = \text{Var}(r_i|r_M > \mu_M) - \beta_i^2\text{Var}(r_M|r_M > \mu_M)$ and $\text{Idio}_i^- = \text{Var}(r_i|r_M < \mu_M) - \beta_i^2\text{Var}(r_M|r_M < \mu_M)$, where we measure idiosyncratic risk against CAPM beta rather than upside and downside betas. Additionally, we test idiosyncratic risk measured against lagged systematic risk – described in the next subsection.

We note that heteroscedasticity of idiosyncratic volatility is closely related to asymmetric cor-

[4] We use normalization by CAPM beta β as a robustness check.

relations. Previous studies, such as Longin and Solnik (2001), Ang and Chen (2002), or Hong et al. (2006) demonstrated that stock indices and returns of individual stocks exhibit higher correlations during negative market moves than during positive market moves. This can be interpreted as the ratio of idiosyncratic to systematic volatility being smaller during negative market moves than during positive market moves, because the correlation coefficient can be written as $\rho = 1/\sqrt{1 + \sigma_i^2/(\beta_i^2 \sigma_M^2)}$, where σ_i^2 is idiosyncratic volatility and σ_M^2 is market volatility. The ratio of idiosyncratic to systematic volatility can be asymmetric simply because upside and downside betas differ, even if upside and downside idiosyncratic risk is the same. We therefore focus on differences in conditional idiosyncratic risk directly, instead of working with conditional correlations.[5]

To measure price delay, we adopt measures introduced by Hou and Moskowitz (2005). In the study by Hou and Moskowitz (2005), the market return represents the systematic news to which individual stock returns respond. Metrics introduced by Hou and Moskowitz (2005) therefore measure *systematic* price delay – the delay in pricing systematic risks.

Following Hou and Moskowitz (2005), we estimate a market model with market returns lagged up to L weeks using weekly stock return data:

$$r_{it} = \alpha_i + \sum_{n=0}^{L} \beta_{in} r_{M,t-n} + \varepsilon_{it}. \tag{8}$$

For most of this study, we follow Hou and Moskowitz (2005) and use weekly lags of up to four weeks, $L = 4$. When working with lags up to four weeks, we use year-long estimation periods that end on the last trading day of June each year. For some portion of the study (as discussed below), we use lags for up to 8 weeks, $L = 8$. When working with lags for up to 8 weeks, we use (overlapping) three-year-long estimation periods. We still estimate all metrics on an annual basis as of the end of June of each year and correct any standard errors for overlapping periods (Newey and West, 1987).

[5]Prior studies of asymmetric correlations used exceedance correlations, where upside and downside correlations are conditioned not only on market moves, as we do in the present study, but also on individual stock returns. Exceedance correlations are defined as $\rho^+ = \rho(r_i, r_M | r_i > \mu_i, r_M > \mu_M)$ and $\rho^- = \rho(r_i, r_M | r_i < \mu_i, r_M < \mu_M)$, where ρ is the Pearson correlation function. Cizeau, Potters, and Bouchaud (2001), Campbell, Forbes, Koedijk, and Kofman (2008), and Foster, Lopatnikova, and Satchell (2020) argue that exceedance correlations need to be used with caution as they can result in false positives, for example when the distribution of idiosyncratic returns is skewed. We therefore use alternative metrics to study idiosyncratic asymmetry.

We use metrics D_1 and D_2 introduced by Hou and Moskowitz (2005) to measure the overall degree of systematic price delay and the average price delay duration, respectively. The metric D_1 is the simplest and most robust; it is defined as:

$$D_1 = 1 - \frac{R_0^2}{R_L^2}, \tag{9}$$

where R_0^2 is the R^2 of single-variable regression of individual stock returns on market returns without lag and R_L^2 is the R^2 of multivariate regression of individual stock returns on unlagged and lagged market returns (with weekly lags of up to L weeks). The price delay metric D_1 is higher when R_L^2 is significantly greater than R_0^2, indicating that lagged market returns have explanatory power relative to unlagged market returns.

The shortcoming of D_1 is that it gives no indication of the duration of average price delay. Metric D_2 helps measure this duration. It is defined as:

$$D_2 = \frac{\sum_{n=1}^{L} n\beta_n}{\sum_{n=0}^{L} \beta_n}. \tag{10}$$

To analyze the asymmetric delay of positive and negative news, we generalize the market model in Eq. (8) to have:

$$r_{it} = \alpha_i + \sum_{n=0}^{\infty} \beta_{in}^{+} r_{M,t-n} \mathcal{O}(r_{M,t-n} - \mu) + \sum_{n=0}^{\infty} \beta_{in}^{-} r_{M,t-n} \mathcal{O}(\mu - r_{M,t-n}) + \varepsilon_{it}, \tag{11}$$

where $\mu \equiv E[r_{Mt}]$ and $\mathcal{O}(\bullet)$ is the Heaviside step function, which helps select days with positive market returns and negative market returns. Using this asymmetric market model, we can define corresponding versions of price delay metrics $D_1^{\pm}$ and $D_2^{\pm}$, which we use for robustness checks.

2.2 Data

We use return and trading volume time series data from the Center for Research in Security Prices (CRSP), fundamental accounting data from Compustat, VIX index time series from Chicago Board Options Exchange (CBOE), and monthly risk free rates from Fama-French database within CRSP.

We use daily return time series for stocks traded on the NYSE, Nasdaq, and Amex during the period between 1963 and 2019, with sharecodes 10 and 11, and aggregate these returns to create weakly return time series, where each week runs Thursday to Wednesday. We eliminate shares that had no trading activity on over 30% of the trading dates on which they were listed. In portfolio sorts and regressions where the book-to-market ratio acts as a control variable, we include each stock only in periods when book values of equity were available for this stock on Compustat (we run robustness checks on stocks with book values unavailable). We use the value weighted index from CRSP to estimate systematic risk factor loadings.

We estimate most metrics on an annual basis on the last trading date of June, using trailing twelve months of return time series measured on a weekly basis. The return time series are aggregated based on daily return time series from CRSP, using Thursday-to-Wednesday week designations. The exceptions are $\beta_n^{\pm}$ shown in Figs. 1 and 2, and $D^{\pm}_{2(8)}$ reported in Table 1, which were estimated using three years of trailing data to accommodate lags of up to 8 weeks. Following Fama and French (1992), we estimate the book-to-market ratio using adjusted book value reported in the preceding year and market capitalization estimated on the last trading day of the preceding year.

2.3 Statistical Summary of Metrics

Table 1 provides a statistical summary of estimated metrics. We report the (equally-weighted) mean and standard deviation of the distribution of estimated across stocks and years and also quartile break points at the 1%, 25%, 50%, 75%, and 99% level. We also report the number of estimates across the sample for each metric.

Panel A reports a statistical summary of basic stock characteristics, based on the Fama and French (1992) three-factor model. As is customary, Size is defined as the logarithm of market capitalization (in millions of US dollars) and the book-to-market ratio is the ratio of book equity (equal to shareholders equity adjusted for deferred taxes and preferred stock) to the market capitalisation of the stock.

Panel B reports statistics for CAPM, downside, and upside betas (β, β^- and β^+). Mean estimated β's across the sample are all close to 1, with β^- slightly higher on average than β^+. Downside and upside betas (β^- and β^+) have slightly more variation than CAPM beta, probably as a result of both underlying variation and higher levels of noise (since approximately half the data are used to estimate $\beta^\pm$ than β for each estimation point).

Panel C reports statistics on measures of beta asymmetry and non-linearity. We report both absolute asymmetry $\beta^- - \beta^+$ and relative asymmetry $(\beta^- - \beta^+)/\bar{\beta}$. Both are positive across the sample on average, with significant variation across sample. We also report statistics for coskewness, which is negative on average for the sample, in line with findings of Harvey and Siddique (2000).

Panel D reports a statistical summary for measures of absolute and relative idiosyncratic risk. We report results for idiosyncratic volatility (Idio), measured as the standard deviation of the residual from regression of individual stock returns on market returns, $\varepsilon_i = r_i - \alpha_i - \beta_i r_M$, and the ratio of idiosyncratic volatility to total volatility (Idio/Vol). We also report statistics for idiosyncratic volatility based on the market model with lagged market returns with $L = 4$ (Idio_4). On average, nearly 90% of individual stock volatility is attributed to idiosyncratic risk and the difference between volatility estimated with respect to the market models with or without lags is small.

Panel E lays out statistics for measures of idiosyncratic asymmetry. We provide three versions of idiosyncratic asymmetry (discussed in more detail in Section 2.1: $(\text{Idio}^+ - \text{Idio}^-)/\text{Idio}$ is based on $\text{Idio}^\pm$ estimated with respect to $\beta^\pm$; $(\text{Idio}^+ - \text{Idio}^-)/\text{Idio}_2$ is based on $\text{Idio}^\pm$ estimated with respect to CAPM β; and $(\text{Idio}^+ - \text{Idio}^-)/\text{Idio}_4$ is based on $\text{Idio}^\pm$ estimated with respect to the asymmetric market model with lags in Eq. (11). On average, idiosyncratic asymmetry is positive.

Panel D summarizes statistics for measures of systematic price delay, described in Section 2.1. The metric D_1 measures to what degree pricing of systematic news is delayed (from 0, which stands for no delay, to 1, which stands for over 4 weeks delay) and D_2 measures the average duration of the delay. A negative D_2 indicates a reversal – a negative correlation with past market moves. The metrics $D^-_{2(8)}$ and $D^+_{2(8)}$ (where the subscript (8) indicates that these metrics were estimated with lags of up to $L = 8$ weeks) measure the duration of delay of negative and positive market news. The delay of negative news on average is significantly shorter than the delay of positive news: 0.467 vs. 1.049, a highly statistically significant difference given the standard deviation of 3.5 and approximately 75,000 data points across 3,300 stocks.

Panel G presents a statistical summary of the moments of the distribution of individual stock returns: volatility (Vol), skewness (Skew), and kurtosis (Kurt). On average, individual stock returns are positively skewed and leptokurtic.

Panel H completes the table with a statistical summary of turnover (Turn) and excess turnover (ΔTurn/Turn), defined as turnover divided by its five-year average.

3 Results

We present the results of our empirical investigation of asymmetric dependence of stock returns and systematic price delay.

3.1 Price Delay of Positive and Negative Systematic News

We start by a direct investigation of differences in price delay of positive and negative news. In this section, we show how the lagged upside and downside beta coefficients $\beta_n^{\pm}$ (defined in Section 2.1, Eq. (11) decline as the lag $n = 0, .., L$, where $L = 8$, increases.

Figure 1 shows the mean lagged downside and upside beta coefficients $\beta_n^{\pm}$ as a function of lag n. We split the stock-periods into quartiles by delay D_1 (normalized every year to account for a gradual decline in average delay from 1963 to 2019) and plot mean lagged betas for the lowest-delay quartile in panel (a) and for the highest-delay quartile in panel (b). Upside betas β_n^+ are represented in blue; downside betas β_n^- – in orange. Error bars are based on a standard error, estimated using approximate clustering (effectively assuming we have 25x fewer data points for each lagged beta, in order to make a highly conservative adjustment for the overlap in three-year long estimation periods and any further cross-correlations between stocks). The error bars represent 95% percentiles.

The key difference between low-delay stocks and high-delay stocks is that low-delay stocks have near-zero correlations with lagged market returns, whereas high-delay stocks have (mostly) positive correlations with lagged market returns. Unlagged betas for low-delay stocks are higher than those for high-delay stocks, supporting the hypothesis that there is initial under-reaction to systematic market moves to in high-delay stocks, which is then subsequently priced in with a lag.

High-delay stocks also exhibit greater asymmetry between downside and upside betas than low-delay stocks, both unlagged betas and betas lagged by n weeks. High-delay stocks have higher unlagged downside betas than upside betas, $\beta^- < \beta^+$. This difference persists and then reverses when for $n > 2$. Lagged upside betas β_n^+ are small, but they are statistically significantly positive for lags up to 8 weeks – nearly two months after the initial systematic shock. By contrast, lagged downside betas β_n^- fall to nearly 9 at $n = 4$, and remain, with some fluctuations, around zero for higher lags. The fluctuations (also seen for low-delay stocks) appear unsystematic, however they are statistically significant: in fact, for low delay stocks the average duration $D^-_{2(8)}$ – defined in Section 2.3 – turns negative (-0.13 vs. $D^+_{2(8)}$ of 0.32), likely reflecting the well-known return reversal phenomenon (e.g., De Bondt and Thaler, 1985). (High-delay stocks exhibit similar duration asymmetries, with mean $D^-_{2(8)} = 1.02$ and $D^+_{2(8)} = 1.52$.)

Figure 2 shows mean lagged betas as a function of the lag n for stocks sorted by size. Panel (a) reports the results for the smallest quartile of stocks; panel (b) reports results for the largest quartile. To form quartiles by size, we first normalized market capitalization annually to account for growth in average market capitalization from 1963 to 2019. Even though the unlagged downside and upside betas. β_0^- and β_0^+ are approximately equal for the smallest and largest stocks, the smallest stocks exhibit a clear systematic price delay and a strong price-delay asymmetry.

For the small stocks, lagged upside beta β_n^+ remains positive for a lag of up to 8 weeks – the highest lag we used in this study. Downside β_n^- is also positive for $n > 0$. At around $n = 4$, β_n^- falls below β_n^+ and then turns negative for $n = 7$ and 8, reflecting return reversals. For the smallest quartile of stocks, the average duration of negative systematic delay $D^-_{2(8)}$ is 0.49, but the duration of positive systematic delay $D^+_{2(8)}$ is 1.13. For the largest stocks, the average duration of negative vs. positive systematic delay is 0.35 vs 0.55 – the delay is shorter, particularly for positive news, and asymmetry of duration is smaller.[6]

3.2 Asymmetry of Stock Returns and Systematic Price Delay

In this section, we report empirical results that demonstrate a strong link between asymmetric dependence of stock returns and systematic price delay. We demonstrate the relationship between stock return asymmetries and price delay using portfolio sorts and then test its statistical significance using Fama-MacBeth regressions.

3.2.1 Portfolio Sorts

Table 2 reports measures of beta and idiosyncratic asymmetry of portfolios sorted by systematic price delay (D_1) and size. We sort the portfolios not only by price delay, but also by size, because both price delay and and asymmetries are higher for small stocks. Previous studies (e.g., Harvey and Siddique, 2000; Ang et al., 2006; Alcock and Hatherley, 2016) have reported that size is one of the most important explanatory variables for asymmetric dependence of stock returns. The two dimensional portfolio sorts allow us to dis-aggregate the effects price delay and other drivers associated with smaller market capitalizations. We form portfolios first using size quintiles; then, within the size quintiles, we form quintiles by systematic price delay. Table 2 report equally weighted average $(\beta^- - \beta^+)/\bar{\beta}$ and $(\text{Idio}^- - \text{Idio}^+)/\text{Idio}$ for each of the resulting 25 portfolios. The table also includes mean values of D_1 and Mcap across price delay and size quintiles ("Sorting factor mean"), reports mean $(\beta^- - \beta^+)/\bar{\beta}$ and $(\text{Idio}^- - \text{Idio}^+)/\text{Idio}$ across size and price delay quintiles ("Sorted factor statistics" – *Mean*) and the differences between the Hi and Lo values within these quintiles ("Sorted factor statistics" – *Hi-Lo*).

Panel A reports equal weighted average beta asymmetry $(\beta^- - \beta^+)/\bar{\beta}$ across the sorted portfolios. Asymmetry rises strongly and monotonically with systematic price delay: In top price-delay quintile, the average beta asymmetry is 0.35, compared with -0.03 in the bottom price-delay quintile. For portfolios sorted by price delay and size, the dependence of $(\beta^- - \beta^+)/\bar{\beta}$ on size is fully

[6] As a robustness check, we run the analysis on data from 1991 to 2019 (a half of the sample). The results are noisier, but similar qualitatively and in magnitude.

subsumed by its dependence on price delay. These results are consistent with the hypothesis that beta asymmetry arises when investors allocate attention away from systematic risk. During these periods, pricing of systematic news is delayed, particularly if the news are positive.

Panel B reports equal weighted average idiosyncratic asymmetry $(\text{Idio}^{-} - \text{Idio}^{+})/\text{Idio}$ across the sorted portfolios. Idiosyncratic asymmetry is positive for portfolios with low-to-moderate price delay, but nearly disappears in the highest price-delay quintile. Again, the dependence of idiosyncratic asymmetry on size is fully subsumed by its dependence on systematic price delay. These results are consistent with the hypothesis that, when investors are focused on idiosyncratic news (to the extent that they focus on idiosyncratic news independently of what the market is doing, which results in no idiosyncratic asymmetry), pricing of systematic news is highly delayed. If idiosyncratic news are of low or moderate interest relative to systematic news, investors focus on idiosyncratic news to a greater extent during market "respites" – periods when macroeconomic news flow is predominantly positive.

Table 3 reports a range of other equal weighed average metrics characterising portfolios sorted by systematic price delay and size. To save space, we report the results only for top and bottom size quintiles.

Panel A summarises the results for CAPM beta β, downside beta β^{-}, and upside β^{+}. The betas exhibit a much stronger dependence on price delay D_1 than on size, and upside beta β^{+} depends on D_1 to a greater extent than downside beta β^{-}.

Panel B is a summary of results for alternative measures of nonlinearity and heteroscedasticity, $\beta^{+} - \beta^{-}$, coskewness, and $(\text{Idio}^{-} - \text{Idio}^{+})/\text{Idio}_4$, described in Section 2.3. These measures exhibit a strong dependence on systematic price delay D_1, similar to that of $(\beta^{-} - \beta^{+})/\bar{\beta}$ and $(\text{Idio}^{-} - \text{Idio}^{+})/\text{Idio}$ reported in Table 2.

Panel C reports the basic characteristics of sorted portfolios: equally weighted average systematic price delay D_1, size (Mcap), and the book-to-market ratio (B/M).

3.2.2 Fama-MacBeth Regressions

Next, we turn to Fama-MacBeth regressions of beta and idiosyncratic asymmetry on systematic price delay and related factors. Fama-MacBeth regressions proceed in two steps: As the first step, we estimate all the metrics and factors for each stock on an annual basis (on the last trading day of June of each year), using twelve month of trailing return data (as described in Section 2.2). As the second step, for each year, we run cross-sectional regressions of measures of beta or idiosyncratic asymmetries on other estimated metrics and factor loadings. We then use the resulting distribution of regression coefficients to conduct statistical tests. We reports the mean regression coefficients of cross-sectional regression along with the t-statistics in brackets and average Adj. R^2 of cross-sectional regressions.

Table 4 summarizes the results: Panel A reports the results of regressions of beta asymmetry $(\beta^- - \beta^+)/\bar{\beta}$ on systematic price delay D_1. The single-variable regression of beta asymmetry on price delay (model 1) confirms a strong link between non-linearity and price delay, with a t statistic of 5.0, indicating a very high level of statistical significance. The link between beta asymmetry and systematic price delay remains highly statistically significant when other relevant variables are added as controls. Model 2 includes controls for size and the book-to-market ratio; model 3, adds a control for turnover. In models 4 and 5, we control for the ratio of idiosyncratic to total volatility (Idio/Vol, strongly correlated with price delay, as we will show in Section 3.3), total volatility (Vol), skewness (Skew), and kurtosis (Kurt) – moments of the distribution of individual returns. These metrics have statistically significant explanatory power for $\Delta\beta/\beta$, with skewness having a particularly strong impact (t-statistic of 5.3). Nevertheless, systematic price delay D_1 retains strong and statistically significant explanatory power for $\Delta\beta/\beta$ even when we control the shape of the distribution of individual stock returns.

Panel B of Table 4 reports the results of regressions of idiosyncratic asymmetry $(\text{Idio}^- - \text{Idio}^+)/\text{Idio}$ on systematic price delay D_1. Just as in the case of beta asymmetry, systematic price delay D_1 has very strong and statistically significant explanatory power for idiosyncratic asymmetry, whether in a single-variable regression or a multiple regressions with controls for size, book-to-market ratio, the ratio of idiosyncratic to total volatility, or the second, third, and fourth moments of the distribution of individual stock returns.

3.3 Systematic Price Delay and Idiosyncratic Risk

In this section, we investigate the hypothesis that systematic price delay increases during periods when idiosyncratic news dominate market participants' attention. We measure the degree of importance of idiosyncratic news using three primary metrics: the ratio of idiosyncratic to total volatility (Idio/Vol), kurtosis (Kurt), and excess turnover ΔTurn/Turn (defined in Section 2.3). We run Fama-MacBeth regressions to study the dependence of systematic price delay metrics D_1 and D_2 (defined in Section 2.1) on these measures of relative importance of idiosyncratic risk, while controlling for other variables, such as size, the book-to-market ratio, turnover, total volatility, and skewness.

Table 5 summarizes the results: in Panel A for D_1 and panel B and for D_2. Both measures of systematic price delay exhibit a strong dependence on the ratio of idiosyncratic to total volatility (Idio/Vol), kurtosis (Kurt), and excess turnover ΔTurn/Turn.

The dependence on the ratio of idiosyncratic to total volatility is particularly strong, with both measures of systematic price delay – D_1 and D_2 – exhibiting highly statistically significant relationships with this metric. This strong dependence supports our hypothesis that pricing of systematic news may be delayed when idiosyncratic news are "front-and-center" in the mind of market participants, although a more mechanical explanation cannot be ruled out: that stocks exhibiting higher delay have relatively higher idiosyncratic risk simply because this risk is measured relatively to the unlagged market factor. The impact from lagged systematic risk is then included into the idiosyncratic component of the idiosyncratic to total volatility ratio.

To tease apart the attention effect from the mechanical effect, we test the dependence of systematic price delay on alternative measures of importance of idiosyncratic risk: kurtosis (Kurt) and excess turnover (ΔTurn/Turn). Both D_1 and D_2 exhibit a strong dependence on both measures of relative importance of idiosyncratic risk. The dependence of D_1 on kurtosis is particularly strong, to the extent it supersedes the impact of excess turnover when the two regressands are combined in a multiple regression. The metric D_2 exhibit a similarly strong and more robust dependence excess turnover and a weaker – although still highly statistically significant, with a t-statistic of 3.3 – dependence on kurtosis. The results support the hypothesis that systematic news are delayed to a greater extent when market participants focus on processing idiosyncratic news.

It is interesting to note that we find a negative association between turnover and price delay (as measured by D_1, but not D_2). This finding may seem surprising; however, higher turnover in a cross-section can result not only from idiosyncratic news, but also from issues such as index and ETF membership of a stock, which would reduce systematic price delay. Excess turnover - which measures the innovation in turnover over a year-long estimation period divided by its five-year moving average – provides a better metric of increase in turnover due to idiosyncratic surprises (although it does still include excess turnover driven by macroeconomic news flow).

3.4 Idiosyncratic Asymmetry and Systematic Volatility

In this section, we investigate the the behavior of *aggregated* equally-weighted beta and idiosyncratic asymmetries during periods of elevated market volatility, low valuations, and low sentiment (Baker and Wurgler (2006)). We conduct longitudinal regressions to test the hypothesis that, during periods of elevated systematic volatility and low systematic valuations, investors pay more attention to systematic news, which should result in higher idiosyncratic asymmetries. We run single-factor regressions of beta asymmetry, idiosyncratic asymmetry, and systematic price delay on the aggregate value-weighted book-to-market ratio, aggregate value-weighted excess turnover, the VIX index, and the Baker-Wurgler Sentiment index. Because the VIX index is only available from 1990, we construct a proxy for the VIX index for use in the period from 1963 to 1990, based on the strong historical relationship between VIX and a combination of the book-to-market ratio and excess turnover. All regressors and regressands have been de-trended.

Table 6 summarizes the results. The table reports coefficients of regression and the t statistics associated with these coefficients. A few of the results are statistically significant and can shed light on the impact of macroeconomic volatility on investor attention.

First, we find that systematic price delay, measured here by D_1, is associated negatively with the proxy for VIX and negatively with Sentiment. When investors focus to a greater extent on systematic news, these news appear to be less delayed.

Second, we find that idiosyncratic asymmetry is associated positively with the aggregate book-to-market ratio: When the market is down, idiosyncratic asymmetry is higher. Idiosyncratic asymmetry is also positively, although more weakly, associated with the VIX index – idiosyncratic risk becomes more asymmetric when markets go through a period of increased volatility.

The results for the dependence of beta asymmetry on macroeconomic factors that measure the dominance of systematic news are not statistically significant. There is a weak positive association between beta asymmetry and excess turnover: when investors are focused primarily on systematic news, idiosyncratic asymmetry increases and investors process more idiosyncratic news on positive market days; this results in a greater acceleration of negative systematic news over positive systematic news. (As discussed in previous sections, beta asymmetry also rises during periods of intense focus on idiosyncratic news, but this effect is difficult to measure on the aggregate basis.)

3.5 Asymmetries of Stock Returns and Idiosyncratic Risk

Having considered the impact of systematic news on beta and idiosyncratic asymmetries in the previous section, in this section we move on to considering the impact of *idiosyncratic* news on the asymmetries. We investigate the dependence of beta and idiosyncratic asymmetries on direct and indirect measures of the relative importance of idiosyncratic news. The most direct measure is the ratio of idiosyncratic to total volatility. More indirect measures include kurtosis of individual stock returns and excess turnover. (We investigated the dependence of systematic price delay on these metrics in Sec. 3.3.)

Table 7 reports the results of Fama-MacBeth regressions of measures of beta and idiosyncratic asymmetry on the ratio of idiosyncratic to total volatility, kurtosis, and excess turnover. All three regressors increase when idiosyncratic news become more important. We control all regressions for size, value, skewness and turnover. The table reports the regression coefficients along with the t-statistics in brackets and average Adj. R^2 of cross-sectional regressions.

Panel A reports the results for beta asymmetry. Beta asymmetry exhibits a strong and highly statistically significant positive relationship with each of the measures of relative importance of idiosyncratic news. It has a strong positive slope with the ratio of idiosyncratic to total volatility, with a t statistic greater than 5, and significant slopes with excess turnover and kurtosis. When investors pay attention to idiosyncratic news, systematic news – particularly positive systematic news – get delayed, and we see greater beta asymmetry.

Panel B reports the results for idiosyncratic asymmetry. Idiosyncratic asymmetry decreases when idiosyncratic news rise in relative importance. Idiosyncratic asymmetry has a negative and highly statistically significant relationship with the ratio of idiosyncratic to total volatility, and kurtosis, and a statistically significant negative relationship with excess turnover. Unlike beta asymmetry, idiosyncratic asymmetry is affected by absolute turnover. While excess turnover measures temporary stock-specific increases in turnover, total turnover can be persistently higher for stocks that are traded for macro reasons (for example, stocks that participate in ETFs and index funds or stand in as proxies for macroeconomic risks). For stocks with higher turnover, idiosyncratic asymmetry is higher and it declines during periods with elevated excess turnover – likely driven by idiosyncratic news.

3.6 Robustness Checks

To ensure that our results are minimally affected by the choice metrics and mechanical correlations based on metric construction, we run a number of robustness checks.

A critical robustness check for our study is to demonstrate that the negative relationship between beta and idiosyncratic risk are not due to construction of these metrics. Mechanical dependencies may have arisen if the two metrics were dependent on each other through, for example, β^- and β^+ regression residuals. To this end, we measure idiosyncratic risk during positive and negative market periods in three ways: Against CAPM β, against β^+ during positive periods and β^- during negative periods, and against $\beta_n^{\pm}$ – lagged betas described in Section 2.1. If the negative relationship between beta and idiosyncratic asymmetry was due to mechanical effects, it would change significantly based on the definitions of these metrics. However, if the asymmetries have are linked via fundamental drivers, such as investor attention, then their negative relationship would persist independently of metric construction choices.

To investigate whether the negative relationship between beta and idiosyncratic asymmetries is robust to metric construction choices, we run Fama-MacBeth regressions of three measures of idiosyncratic asymmetry on two measures of beta asymmetry. We include the results of regressions without controls and with controls for size, value, and price delay.

Table 8 summarizes the results. Panel A reports the results for the measure of idiosyncratic volatility where conditional idiosyncratic volatility during negative and positive market weeks was estimated relatively to CAPM β. Panel B reports the results for idiosyncratic volatility, where conditional idiosyncratic volatilities were estimated relative to β^+ during positive market weeks and β^- during negative market weeks. Panel C reports the results for idiosyncratic volatility where idiosyncratic risk was measured using residuals of regression of individual stock returns on lagged market returns (Eq. 8), conditioned on positive and negative market moves.

The dependence of idiosyncratic asymmetry on beta asymmetry is largely unaffected by construction of the idiosyncratic volatility metric or whether beta asymmetry is absolute $(\beta^- - \beta^+)$ or normalized by CAPM β $((\beta^- - \beta^+)/\bar{\beta})$. The negative relationship is weakly mediated by systematic price delay D_1 – the addition of this metric reduces the slope and statistical significance of the negative relationship between idiosyncratic and beta asymmetry. This is to be expected since lower delay means higher attention to systematic risk, and therefore lower beta asymmetry.

4 Corporate Finance Implications

4.1 Investor Attention and Corporate Communications

Our results add to the literature confirming that investors' limited attention affects the incorporation of information into asset prices. Additionally, we demonstrate that not only do investors have limited attention, they also tend to prioritize negative over positive news.

These conclusions have material implications for investors and corporations. They reinforce the need for clear and timely corporate communications and clear and enforceable timely disclosure rules and regulations.

4.2 Beta Estimation and Price Delay

CAPM β plays a critical role in corporate capital budgeting decisions, but, for many companies, CAPM β estimates can vary dramatically (by up to a factor of 2x) depending on return sampling frequency (Gilbert et al., 2014). CAPM β estimated using lower sampling frequencies (e.g. quarterly or annual) – if a sufficiently long history of returns is available – provides a more accurate estimate of beta relevant to corporate capital budgeting than beta estimated using higher sampling frequencies (e.g. daily). But not many corporations have a sufficiently long and sufficiently stationary return history for accurate beta estimation using low-frequency returns. As a result, CAPM beta is commonly estimated using higher-frequency data.

The dependence of CAPM beta β on price delay (see, e.g. Table 3) sheds light on why beta estimates depend on return sampling frequency and may help improve beta estimates for corporations. When pricing of systematic news is delayed, contemporaneous regressions of individual stock returns on unlagged market returns capture only a fraction of the individual stock's reaction to the news, suppressing the estimate of CAPM beta. (Classic corrections of (Scholes and Williams, 1977) and (Williams, 1977) under-correct for this effect when high-frequency returns are used.)

We can use our understanding of the origins of the differences between high-frequency and low-frequency beta estimates to correct high-frequency data in cases where there is insufficient history to obtain accurate low-frequency CAPM beta estimates. Price delay induces individual stock returns autocorrelations. Using these autocorrelations and the correction derived by Hong and Satchell (2014), a more accurate CAPM beta can be estimated using higher-frequency return data.

5 Conclusions

If investors have limited attention, how do they prioritize this attention? Prior theoretical and empirical research demonstrates that a rational investor with limited attention focus first on two types of information: private information and information that affects the largest fraction of their portfolio (see, e.g. Kacperczyk et al., 2016). Our empirical results point to an additional criterion for priotization: Investors appear to prioritize negative over positive information.

We establish several empirical facts: First, using Hou and Moskowitz (2005) systematic price delay metrics generalized to capture the differences between delay of positive and negative news, we show that negative news are priced in faster than positive news. Second, we show that, when pricing of systematic news is delayed, stock returns have a higher downside beta β^- than upside beta β^+ with market returns. Third, we demonstrate that investors are more likely to pay attention to idiosyncratic news when market returns are positive than when they are negative, unless idiosyncratic risk are so important that they cause systematic price delay. Fourth, we show that systematic price delay – the delay in pricing of systematic news – increases during periods when idiosyncratic news rise in prominence (these periods are marked by increased ratio of idiosyncratic to total volatility, high kurtosis, and high excess turnover). Fifth, we demonstrate that beta asymmetry rises and idiosyncratic asymmetry falls when idiosyncratic news are important, consistently with the attention prioritization hypothesis: When investors focus on idiosyncratic news, they price in the news independently of whether the rest of the market is positive or negative. This leaves less attention to be allocated to systematic news, which gets allocated to predominantly negative systematic news, causing a large delay in pricing positive systematic news. Last, we run robustness checks to ensure that the strong statistical relationships we find between beta and idiosyncratic asymmetry, and the asymmetries and price delay cannot be explained by mechanical measurement effects. We re-run our analysis with alternative definitions of all metrics and obtain quantitatively and qualitatively similar results.

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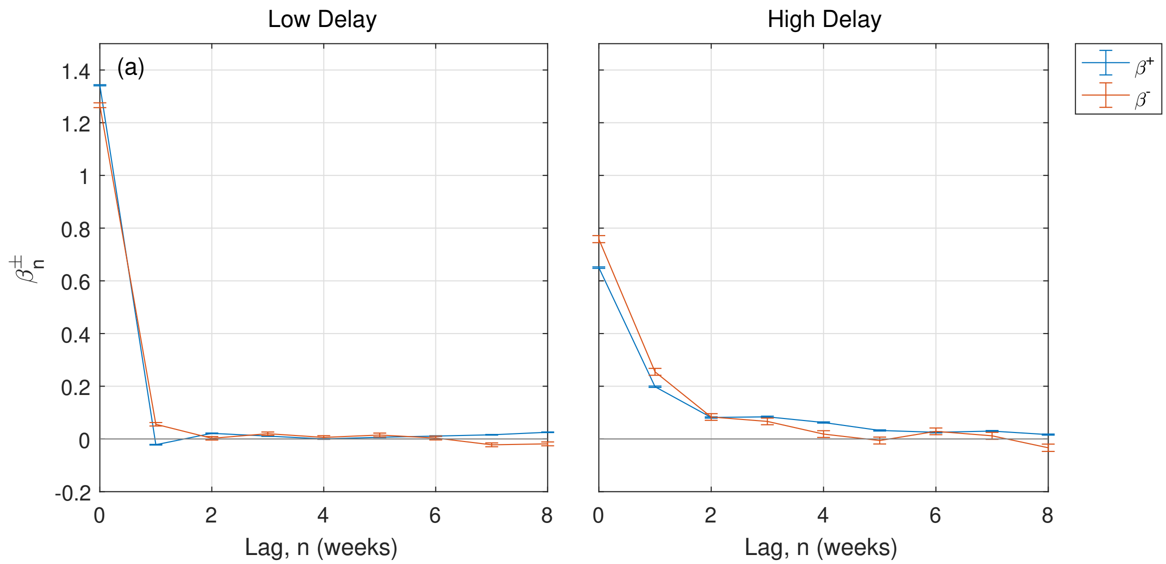

Figure 1: Lagged β_n^+ and β_n^- for stocks with (a) low and (b) high systematic price delay (bottom and top quartiles).

We estimate β_n^+ (blue) and β_n^- (orange) stocks traded on NYSE/Nasdaq/Amex between 1963 and 2019. The lagged upside and downside betas, $\beta_n^{\pm}$, were estimated annually at July 1 using lagged three years of weekly stock and market returns. Delay n is measured in weeks. Error bars represent 95% percentiles; standard errors are estimated using approximate clustered errors (described in Section 3.1). Stocks exhibiting highest systematic delay have (1) lower unlagged betas; (2) higher unlagged downside beta than upside beta; and (3) higher upside beta than downside beta (on average) for higher lags, $n > 2$. Stocks exhibiting lowest systematic delay have higher unlagged betas and near-zero lagged betas.

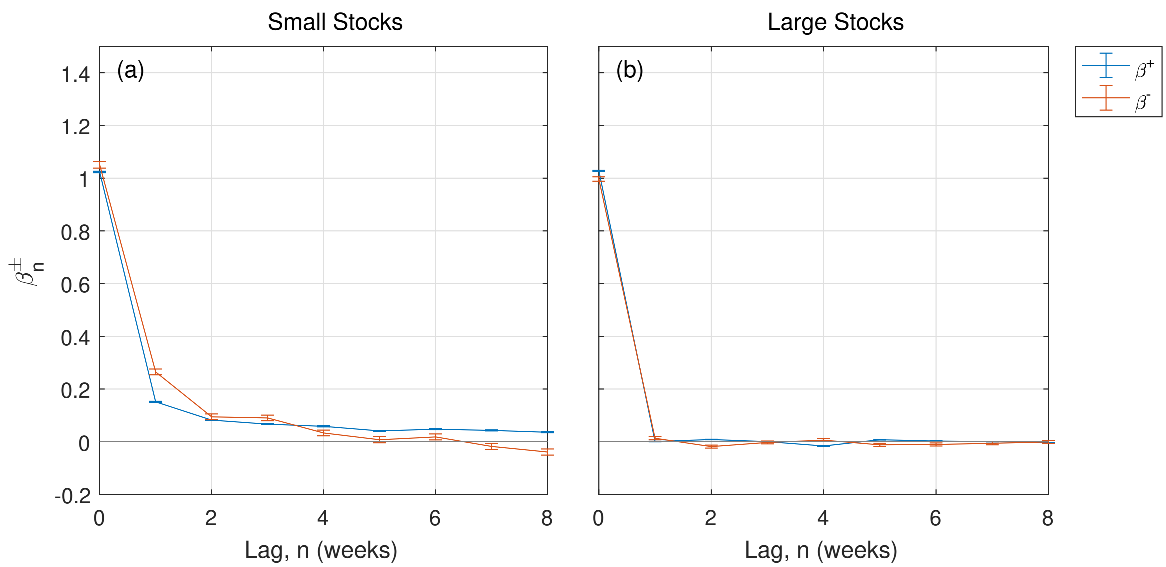

Figure 2: Lagged β_n^+ and β_n^- for (a) small and (b) large stocks (bottom and top quartiles). We estimate β_n^+ (blue) and β_n^- (orange) stocks traded on NYSE/Nasdaq/Amex between 1963 and 2019. The lagged upside and downside betas, $\beta_n^{\pm}$, were estimated annually at July 1 using lagged three years of weekly stock and market returns. Delay n is measured in weeks. Error bars represent 95% percentiles; standard errors are estimated using approximate clustered errors (described in Section 3.1). Smallest stocks (1) similar unlagged betas to large stocks; (2) higher unlagged downside beta than upside beta; and (3) higher upside beta than downside beta for higher lags, $n > 2$. Larger stocks have near-zero lagged betas.

Table 1: Descriptive factor statistics. This table presents statistics of estimated stock characteristics, factor loadings, and other metrics. The table provides the mean (Mean), standard deviation (Std), percentile breakpoints at 1%, 25%, 50%, 75%, and 99%. The study used daily return time series of stocks traded on NYSE/Amex/Nasdaq traded during the period between 1963 and 2019, with sharecodes 10 and 11.

Factors	Mean	Std	Percentile break points					N
			1%	25%	50%	75%	99%	
Panel A: Size and book-to-market ratio								
Mcap	6.173	1.98	1.961	4.767	6.153	7.486	11.008	79617
B/M	0.855	0.87	0.061	0.397	0.668	1.066	3.715	76567
Panel B: CAPM, downside, and upside beta								
β	1.042	0.66	-0.260	0.601	0.977	1.400	2.962	84956
β^-	1.076	0.93	-1.051	0.521	1.008	1.553	3.763	84956
β^+	1.004	1.01	-1.258	0.404	0.919	1.518	3.957	84956
Panel C: Beta asymmetry and (and general non-linearity)								
$\beta^- - \beta^+$	0.072	1.41	-3.675	-0.640	0.055	0.762	4.001	84956
$(\beta^- - \beta^+)/\bar{\beta}$	0.127	1.67	-5.042	-0.637	0.050	0.813	5.602	82121
Cosk	-0.347	12.37	-31.031	-7.914	-0.591	7.050	32.226	84956
Panel D: Idiosyncratic risk								
$\frac{\text{Idio}}{\text{Vol}}$	0.886	0.10	0.586	0.832	0.909	0.963	1.000	84956
Idio	0.047	0.03	0.015	0.030	0.041	0.056	0.147	84956
Idio_4	0.042	0.02	0.013	0.026	0.036	0.050	0.130	84956
Panel E: Idiosyncratic asymmetry								
$(Idio^+ - Idio^-)/Idio$	0.062	0.30	-0.687	-0.136	0.068	0.269	0.751	84956
$(Idio^+ - Idio^-)/Idio_2$	0.064	0.30	-0.676	-0.132	0.069	0.268	0.745	84956
$(Idio^+ - Idio^-)/Idio_4$	0.045	0.28	-0.617	-0.138	0.050	0.236	0.667	84956
Panel F: Price delay								
D_1	0.352	0.28	0.015	0.127	0.270	0.524	0.996	84956
D_2	0.283	2.23	-7.457	-0.484	0.467	1.222	7.387	80247
$D^-_{2(8)}$	0.467	3.49	-8.988	-1.380	0.848	2.575	8.758	74976
$D^+_{2(8)}$	1.049	3.36	-8.693	-0.622	1.353	2.972	8.991	76479
Panel G: Moments of the distribution of individual stock returns								
Vol	0.053	0.03	0.017	0.034	0.047	0.063	0.159	84956
Skew	0.344	0.87	-1.782	-0.117	0.283	0.727	3.250	84956
Kurt	4.810	3.36	2.201	3.107	3.845	5.195	19.665	84956
Panel H: Turnover								
Turn	0.868	1.23	0.000	0.181	0.479	1.101	5.708	88583
$\frac{\Delta\text{Turn}}{\overline{\text{Turn}}}$	0.962	0.58	0.000	0.675	0.994	1.285	2.542	88929

Table 2: Conditional factor loadings sorted by size and price delay. This table reports portfolio sorts for factor loadings estimated for NYSE/Amex/Nasdaq traded stocks 1963-2018 (sharecodes 10 anbd 11). Factor loadings and price delay metric D_1 were estimated annually, at June 30, using $T = 12$ months of trailing weekly return time series. Weekly return times series are based on daily return time series, total weekly returns are estimated on a Thursday-to-Wednesday basis.

	Sorted portfolios					Sorted factor statistics		Sorting factor mean	
	Lo D_1	2	3	4	Hi D_1	Mean	Hi-Lo	Mcap	D_1
Panel A: $(\beta^- - \beta^+)/\bar{\beta}$									
Lo Mcap	-0.02	0.03	0.07	0.17	0.33	0.11	0.35	4.01	0.35
2	-0.01	0.02	0.07	0.25	0.39	0.14	0.41	5.27	0.35
3	-0.03	0.01	0.06	0.19	0.33	0.11	0.36	6.12	0.35
4	-0.02	0.00	0.09	0.22	0.33	0.13	0.35	7.03	0.35
Hi Mcap	-0.04	0.01	0.05	0.16	0.36	0.11	0.40	8.51	0.35
Sorted factor statistics									
Mean	-0.03	0.01	0.07	0.20	0.35				
Hi-Lo	-0.02	-0.03	-0.02	-0.01	0.03				
Panel B: $(Idio^+ - Idio^-)/Idio$									
Lo Mcap	0.06	0.08	0.07	0.07	0.01	0.06	-0.05	4.01	0.35
2	0.06	0.08	0.08	0.07	0.02	0.06	-0.04	5.27	0.35
3	0.08	0.07	0.07	0.06	0.02	0.06	-0.06	6.12	0.35
4	0.07	0.07	0.08	0.06	0.02	0.06	-0.05	7.03	0.35
Hi Mcap	0.07	0.08	0.09	0.08	0.01	0.07	-0.06	8.51	0.35
Sorted factor statistics									
Mean	0.07	0.08	0.08	0.07	0.02				
Hi-Lo	0.01	0.01	0.01	0.01	-0.00				
Sorting factor mean									
D_1	0.06	0.15	0.27	0.46	0.81				
Mcap	6.26	6.26	6.19	6.15	6.09				

Table 3: Conditional factor loadings sorted by size and price delay: additional factors. This table reports average factor loadings of portfolios sorted by size and price delay. There results for the top and bottom quintile portfolios by size are reported. Factor loadings were estimated annually, on June 30, using $T = 12$ months of trailing weekly return time series, for NYSE/Amex/Nasdaq traded stocks 1963-2018 (sharecodes 10 anbd 11). Weekly return times series were based on daily return time series, aggregated on Thursday-to-Wednesday basis. The table reports results for CAPM beta (β); downside beta (β^-); upside beta (β^+); the difference between downside and upside beta ($\beta^- - \beta^+$); coskewness – shown here multiplied by 100 (Cosk); an alternative measure of heteroscedasticity ($(Idio^+ - Idio^-)/Idio_4$), where idiosyncratic risk was estimated based on trailing positive and negative market returns; systematic price delay (D_1); size, measured as log of market capitalization (Mcap); and the book to market ratio (B/M).

Portfolio	Factor average					
	Panel A: CAPM, downside, and upside betas					
	β		β^-		β^+	
	Lo Mcap	Hi Mcap	Lo Mcap	Hi Mcap	Lo Mcap	Hi Mcap
Lo D_1	1.47	1.34	1.43	1.30	1.51	1.37
2	1.33	1.24	1.32	1.22	1.33	1.25
3	1.20	1.09	1.20	1.11	1.19	1.06
4	0.96	0.86	1.04	0.92	0.89	0.81
Hi D_1	0.42	0.40	0.54	0.51	0.29	0.28
	Panel B: Alternative measures of nonlinearity and heteroscedasticity					
	$\beta^- - \beta^+$		Cosk†		$(Idio^+ - Idio^-)/Idio_4$	
	Lo Mcap	Hi Mcap	Lo Mcap	Hi Mcap	Lo Mcap	Hi Mcap
Lo D_1	-0.08	-0.07	0.82	1.21	0.05	0.06
2	-0.01	-0.03	0.30	0.61	0.06	0.06
3	0.02	0.04	-0.25	-0.26	0.05	0.07
4	0.15	0.11	-0.98	-0.89	0.05	0.06
Hi D_1	0.25	0.23	-1.82	-1.35	0.00	0.00
	Panel C: Systematic price delay, size, and book-to-market ratio					
	D_1		Mcap		B/M	
	Lo Mcap	Hi Mcap	Lo Mcap	Hi Mcap	Lo Mcap	Hi Mcap
Lo D_1	0.06	0.06	4.04	8.70	1.35	0.59
2	0.15	0.15	4.05	8.63	1.12	0.61
3	0.27	0.27	4.00	8.54	1.17	0.63
4	0.46	0.46	4.00	8.39	1.15	0.63
Hi D_1	0.81	0.81	3.97	8.30	1.16	0.62

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Table 4: Fama-MacBeth Regressions of Asymmetric Dependence Factors on Price Delay. This table reports results of Fama-MacBeth regressions of estimated Asymmetric Dependence factor loadings on measures and drivers of price delay; the t statistic for each slope is provided in brackets. Adjusted R^2, averaged across estimation period, is reported for each regression model. Factor loadings are estimated annually, January to December, using weekly returns. Mcap (log of market capitalization) and B/M (book-to-market ratio) were estimated as of the end December of the calendar year preceding the start of the estimation period.

Models	Regressors									Avg Adj R^2
	Int	D_1	Mcap	B/M	Turn	Idio/Vol	Vol	Skew	Kurt	
Panel A: $(\beta^- - \beta^+)/\bar{\beta}$										
(1)	-0.150	0.815								0.03
	[-3.0]	[5.0]								
(2)	0.011	0.731	-0.025	0.016						0.18
	[0.1]	[4.9]	[-1.4]	[0.9]						
(3)	-0.018	0.728	-0.024	0.017	0.038					0.21
	[-0.1]	[4.9]	[-1.4]	[0.9]	[0.8]					
(4)	-0.573	0.554	-0.016	0.015	0.045	0.642				0.21
	[-2.6]	[3.6]	[-0.9]	[0.8]	[1.0]	[2.6]				
(5)	-0.750	0.559	-0.019	0.020	0.001	0.752	2.312	-0.229	0.017	0.23
	[-3.1]	[3.6]	[-1.3]	[1.1]	[0.0]	[2.6]	[2.3]	[-5.3]	[2.4]	

Table 4: (Continued.)

Models	Regressors									Avg Adj R^2
	Int	D_1	Mcap	B/M	Turn	Idio/Vol	Vol	Skew	Kurt	
Panel B: $(Idio^{+} - Idio^{-})/Idio$										
(1)	0.096	-0.094								0.01
	[5.2]	[-4.5]								
(2)	0.173	-0.112	-0.012	-0.001						0.14
	[6.2]	[-4.9]	[-5.6]	[-0.2]						
(3)	0.166	-0.112	-0.012	-0.001	0.010					0.16
	[6.1]	[-4.9]	[-5.6]	[-0.1]	[2.0]					
(4)	0.336	-0.073	-0.014	-0.000	0.008	-0.193				0.17
	[5.4]	[-3.6]	[-6.0]	[-0.1]	[1.6]	[-3.9]				
(5)	0.261	-0.093	-0.002	-0.008	-0.001	-0.205	0.368	0.130	-0.008	0.25
	[4.1]	[-4.7]	[-1.1]	[-2.4]	[-0.3]	[-3.8]	[2.4]	[6.4]	[-4.7]	

Table 5: Price Delay and Stock Characteristics. This table reports results of Fama-MacBeth regressions of the Price Delay metric D_1 on stock Characteristics for stocks traded on NYSE/AMEX/Nasdaq in the period between 1963 and 2019 (sharecodes 10 and 11). Price delay (D_1), Volatility (Vol), Skewness (Skew), Kurtosis (Kurt) and the ratio of idiosyncratic to total volatility (Idio/Vol) were estimated annually, January to December, using weekly returns. Size (log of market capitalization) and B/M (book-to-market ratio) were estimated as of the end December of the calendar year preceding the start of the estimation period. The t statistic for each regression coefficient is provided in brackets. Adjusted R^2, averaged across estimation period, is reported for each regression model.

Models	Regressors									Avg Adj R^2
	Int	Mcap	B/M	$\frac{\text{Idio}}{\text{Vol}}$	Turn	Vol	Skew	Kurt	$\frac{\Delta\text{Turn}}{\text{Turn}}$	
Panel A: D_1										
(1)	0.609	-0.047	0.014							0.23
	[7.0]	[-6.7]	[2.7]							
(2)	0.633	-0.048	0.011		-0.049					0.26
	[7.0]	[-6.7]	[2.1]		[-3.7]					
(3)	-1.725	-0.005	0.006	2.325	-0.011					0.61
	[-6.4]	[-3.9]	[2.5]	[6.7]	[-3.5]					
(4)	-1.724	-0.003	0.004	2.279	-0.013	0.142	0.000	0.005		0.62
	[-6.4]	[-2.9]	[1.8]	[6.7]	[-3.6]	[1.3]	[0.0]	[5.9]		
(5)	0.610	-0.050	0.010		-0.061				0.036	0.26
	[6.9]	[-6.8]	[2.0]		[-3.9]				[4.8]	
(6)	-1.722	-0.003	0.004	2.280	-0.012	0.141	-0.000	0.005	-0.002	0.62
	[-6.4]	[-2.9]	[1.8]	[6.7]	[-3.5]	[1.3]	[-0.0]	[5.9]	[-1.2]	
Panel B: D_2										
(1)	1.135	-0.156	0.042							0.13
	[6.0]	[-6.2]	[1.5]							
(2)	1.129	-0.156	0.038		-0.046					0.15
	[6.0]	[-6.2]	[1.4]		[-1.3]					
(3)	-4.827	-0.049	0.030	5.838	0.024					0.18
	[-5.6]	[-3.1]	[1.4]	[5.9]	[0.8]					
(4)	-4.873	-0.043	0.034	5.674	-0.003	1.279	-0.069	0.025		0.19
	[-5.8]	[-2.8]	[1.5]	[5.9]	[-0.1]	[1.2]	[-2.6]	[3.4]		
(5)	0.966	-0.157	0.041		-0.098				0.185	0.15
	[5.4]	[-6.2]	[1.5]		[-2.6]				[4.6]	
(6)	-4.935	-0.043	0.037	5.656	-0.024	1.152	-0.069	0.025	0.091	0.19
	[-5.8]	[-2.9]	[1.7]	[5.9]	[-0.9]	[1.1]	[-2.7]	[3.3]	[3.3]	

Table 6: Macro drivers, price delay, and asymmetries. This table coefficients of single-factor longitudinal regressions and corresponding t-statistics (in brackets) of de-trended equally weighted measures of systematic and idiosyncratic price delay on de-trended aggregate market variables: value-weighted book-to-market ratio (B/M), value-weighted Excess Turnover ($\Delta Turn/Turn$), the VIX index (VIX), a proxy for the VIX index (VIX proxy), and Sentiment. Asymmetry factor loadings are estimated annually, January to December, using weekly returns (based on daily returns of stocks that traded on NYSE/Nasdaq/Amex, aggregated on a Thursday-to-Wedesday basis). The book-to-market ratio was estimated as of the end December of the calendar year preceding the start of the estimation period. All data except VIX are available from 1963-2019. VIX is available from 1990. We use the strong statistically-significant relationship between VIX, the book-to-market ratio, and turnover to construct a "VIX proxy" for the period between 1963 and 1990.

Regressand (EW)	Coefficients of Single-factor Regression				
	B/M	ΔTurn/Turn	VIX	VIX proxy	Sentiment
$(Idio^{+} - Idio^{-})/Idio$	0.0062	0.0056	0.0002	0.0001	-0.0005
	[1.90]	[0.98]	[0.72]	[0.61]	[-0.54]
$(\beta^{-} - \beta^{+})/\bar{\beta}$	0.0215	0.0521	0.0002	0.0009	0.0009
	[1.08]	[1.47]	[0.14]	[0.78]	[0.44]
D_1	-0.0082	-0.0047	-0.0002	-0.0007	0.0030
	[-1.33]	[-0.42]	[-0.46]	[-2.16]	[1.6]

Table 7: Asymmetries and idiosyncratic news. This table reports results of Fama-MacBeth regressions of measures of asymmetric dependence on Price delay (D_1), Turnover (Turn), the ratio of Idiosyncratic to total volatility (Idio/Vol) and other stock characteristics for stocks traded on NYSE/AMEX/Nasdaq in the period between 1963 and 2019 (sharecodes 10 and 11). Price delay (D_1), the ratio of idiosyncratic to total volatility (Idio/Vol), Turnover, Volatility (Vol), Skewness (Skew), Kurtosis (Kurt) and were estimated annually, January to December, using weekly returns. Size (log of market capitalization) and B/M (book-to-market ratio) were estimated as of the end December of the calendar year preceding the start of the estimation period. The t statistic for each regression coefficient is provided in brackets. Adjusted R^2, averaged across estimation period, is reported for each regression model.

Models	Regressors								Avg Adj R^2
	Int	$\frac{\text{Idio}}{\text{Vol}}$	Turn	$\frac{\Delta\text{Turn}}{\text{Turn}}$	Kurt	Skew	Mcap	B/M	
Panel A: $(\beta^- - \beta^+)/\bar{\beta}$									
(1)	-1.674	2.116					-0.020	0.016	0.17
	[-4.5]	[5.1]					[-1.2]	[0.8]	
(2)	0.417		-0.005				-0.057	0.023	0.18
	[2.7]		[-0.1]				[-2.9]	[1.2]	
(3)	0.352		-0.035	0.081			-0.059	0.021	0.19
	[2.3]		[-0.8]	[3.0]			[-2.9]	[1.1]	
(4)	0.433				0.032	-0.223	-0.070	0.032	0.17
	[2.9]				[3.8]	[-5.3]	[-3.5]	[1.7]	
Panel B: $(Idio^+ - Idio^-)/Idio$									
(1)	0.486	-0.382					-0.013	-0.001	0.14
	[5.6]	[-5.1]					[-5.9]	[-0.2]	
(2)	0.095		0.019				-0.006	-0.002	0.15
	[5.6]		[3.1]				[-3.7]	[-0.4]	
(3)	0.104		0.026	-0.017			-0.006	-0.001	0.16
	[5.8]		[3.3]	[-2.7]			[-3.1]	[-0.3]	
(4)	0.048				-0.009	0.129	0.004	-0.010	0.21
	[3.9]				[-4.7]	[6.4]	[2.0]	[-2.6]	

Table 8: Beta vs. Idiosyncratic Asymmetries. This table reports results of Fama-MacBeth regressions of estimated heteroscedasticity measures ($Idio^+ - Idio^-/Idio$) on measures of non-linearity ($\beta^- - \beta^+$ and $(\beta^- - \beta^+)/\bar{\beta}$. heteroscedasticity $Idio^+ - Idio^-/Idio$ is measured three ways: (1) For $Idio^+ - Idio^-/Idio$, idiosyncratic risk on positive and negative market weeks was estimated relative to CAPM β; (2) For $Idio^+ - Idio^-/Idio_2$, idiosyncratic risk was estimated relative to β^+ on positive and β^- on negative market weeks; (3) For $Idio^+ - Idio^-/Idio_4$, idiosyncratic risk was measured using the residual of the regression of individuals stock returns on delayed market returns. For each regression coefficient, the t statistic is provided in brackets. Adjusted R^2, averaged across estimation period, is reported for each regression model. Factor loadings are estimated annually, January to December, using weekly returns. Size (log of market capitalization) and B/M (book-to-market ratio) were estimated as of the end December of the calendar year preceding the start of the estimation period.

Models	Regressors						Avg Adj R^2
	Int	$\beta^- - \beta^+$	$(\beta^- - \beta^+)/\bar{\beta}$	Mcap	B/M	D_1	
Panel A: $(Idio^+ - Idio^-)/Idio$							
(1)	0.064	-0.012					0.01
	[5.0]	[-4.5]					
(2)	0.111	-0.012		-0.007	-0.002		0.13
	[5.9]	[-4.7]		[-4.1]	[-0.5]		
(3)	0.173	-0.010		-0.012	-0.001	-0.106	0.15
	[6.2]	[-4.3]		[-5.6]	[-0.1]	[-4.8]	
(4)	0.068		-0.008				0.06
	[5.1]		[-4.0]				
(5)	0.122		-0.009	-0.008	-0.002		0.17
	[6.2]		[-4.3]	[-4.9]	[-0.4]		
(6)	0.171		-0.007	-0.012	-0.000	-0.091	0.18
	[6.2]		[-3.9]	[-5.7]	[-0.0]	[-4.3]	
Panel B: $(Idio^+ - Idio^-)/Idio_2$							
(1)	0.062	-0.013					0.01
	[4.9]	[-4.2]					
(2)	0.110	-0.013		-0.007	-0.002		0.14
	[5.8]	[-4.3]		[-4.2]	[-0.6]		
(3)	0.173	-0.012		-0.012	-0.001	-0.106	0.15
	[6.1]	[-4.0]		[-5.6]	[-0.2]	[-4.8]	
(4)	0.066		-0.009				0.06
	[5.0]		[-3.8]				
(5)	0.122		-0.009	-0.009	-0.002		0.18
	[6.1]		[-4.0]	[-5.0]	[-0.4]		
(6)	0.171		-0.008	-0.013	-0.000	-0.091	0.18
	[6.1]		[-3.6]	[-5.7]	[-0.1]	[-4.2]	

Table 8: (Continued.)

Models	Regressors						Avg Adj R^2
	Int	$\beta^- - \beta^+$	$(\beta^- - \beta^+)/\bar{\beta}$	Mcap	B/M	D_1	
Panel C: $(Idio^+ - Idio^-)/Idio_4$							
(1)	0.045	-0.008					0.00
	[4.5]	[-4.0]					
(2)	0.090	-0.009		-0.007	-0.003		0.13
	[6.2]	[-4.6]		[-4.8]	[-0.7]		
(3)	0.152	-0.007		-0.012	-0.001	-0.106	0.14
	[6.5]	[-3.9]		[-6.4]	[-0.2]	[-5.6]	
(4)	0.048		-0.006				0.05
	[4.7]		[-3.5]				
(5)	0.100		-0.006	-0.008	-0.002		0.17
	[6.4]		[-4.1]	[-5.4]	[-0.5]		
(6)	0.152		-0.005	-0.012	-0.000	-0.096	0.18
	[6.5]		[-3.4]	[-6.4]	[-0.1]	[-5.2]	

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