Information content and other characteristics of the daily cross-sectional dispersion in stock returns

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Abstract

We study the cross-sectional dispersion in daily stock returns, or daily return dispersion (RD). Our primary empirical contribution is to demonstrate that RD contains reliable incremental information about the future traditional volatility of both firm-level and portfolio-level returns. The relation between RD and future stock volatility is pervasive across time and across different industry portfolios, size-based portfolios, and beta-based portfolios. Further, our results suggest that RD contains more incremental information about the future volatility of firm-level stock returns than do lagged market-level return shocks. To further characterize RD and assist in interpretation, we also document how dispersion varies with stock turnover and macroeconomic news.

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1. Introduction

While the literature on time-varying traditional volatility in stock returns is voluminous, the study of cross-sectional return dispersion is relatively limited. In this

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paper, we study the cross-sectional dispersion in daily stock returns, or daily return dispersion (RD). Our primary empirical goal is to demonstrate the incremental information in RD for the subsequent traditional volatility of both firm-level and portfolio-level daily returns. Our study also serves to document the time-series behavior of daily RD and the relation of daily dispersion to other variables such as stock turnover and macroeconomic news.

Despite the lack of direct theoretical work on the issue, intuition and prior empirical work suggest several likely reasons to suspect that RD may contain incremental information about the future traditional volatility of stock returns. First, from a statistical perspective, findings in Campbell et al. (2001) suggest that the time-variation in aggregate firm-level volatility does not simply mirror the time-variation in market-level volatility. This implies that a RD measure may provide information that is incrementally informative about future stock volatility.

For illustration, consider a simple 3-firm stock market with conditional firm volatilities that are persistent in the time-series and that share a commonality across firms. Then, assume that on a given day the stock returns in the stock market are 15%, −15%, and 1% for Firms A, B, and C, respectively. For Firm C, a volatility model with explanatory terms that only include the lagged own-firm return shocks and aggregate market-return shocks would not capture the high firm-level volatility environment (suggested by the very large absolute returns for Firms A and B). Another statistical possibility is that RD may capture information about multiple common-factor shocks that is not adequately represented by only the market-return shock. In this sense, RD may provide information to help identify the unobservable volatility environment.

Second, RD may have economic interpretations that suggest a positive association with future traditional volatility. For example, one possibility is that RD reflects firm-level information flows which cluster in time. If so, then RD might contain incremental information about future volatility, including market-level volatility if the future firm information flows are cross-sectionally correlated. Relatedly, Bekaert and Harvey (1997) study cross-country variations in market-level stock volatility and find that a higher return dispersion is associated with higher market volatility for countries where the market capitalization to GDP ratio is relatively high (typical in more developed markets). They

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2 Studies of traditional conditional volatility examine the time-series deviation of stock returns from their mean. In contrast, we study the daily dispersion of disaggregate stock returns about the market return. The few volatility studies that have used dispersion-type metrics in some capacity have only evaluated the monthly return horizon and market-level volatility (see, e.g., Bekaert and Harvey, 1997, 2000; Stivers, 2003). Our primary measure for return dispersion is a day’s cross-sectional standard deviation of firm-level stock returns.

3 By incremental, we mean information beyond that captured by widely-used conditional volatility models that rely solely upon a single series or limited number of series of lagged return shocks (such as a firm-level volatility model where the lagged own-firm return shocks and lagged market-level return shocks are explanatory variables). Of course, a multivariate GARCH system might be used to incorporate cross-firm volatility information into volatility models for a few return series. However, it would certainly be impractical to estimate a simultaneous multivariate volatility model for the set of 1081 individual firm returns in this study. In addition, as Campbell et al. (2001) note, "Multivariate volatility models are notoriously complicated and difficult to estimate" (p. 3).
suggest that dispersion may reflect the magnitude of firm-level information flows for these countries.4

Another possible economic interpretation is that RD may be positively associated with the underlying economic uncertainty and/or dispersion-in-beliefs about the market signal or market state.5 Relatedly, we find a sizable positive correlation both between the unexpected components of daily RD and stock turnover and between the expected components of daily RD and turnover. We also find that RD tends to be relatively low on days when macroeconomic news is announced. If: (1) higher turnover is associated with more diverse beliefs and higher uncertainty, and (2) macroeconomic-news releases tend to resolve uncertainty; then our findings relating RD to turnover and macroeconomic news provide some support to this potential economic interpretation.

In this paper, we study the conditional volatility of daily stock returns at both the firm and portfolio level. We begin by studying the daily return volatility for 1081 NYSE firms, which is a much larger sample than earlier firm-level volatility studies that have used GARCH-type empirical models (see, e.g., Engle and Lee, 1993; Lamoureux and Lastrapes, 1990). We propose and estimate a new firm-level conditional volatility model that features three distinct explanatory components: (1) the specific firm’s conditional idiosyncratic volatility, (2) the conditional market-level volatility (formed from the time-series of lagged market-return shocks), and (3) a conditional cross-sectional volatility, or CSV (formed from the time-series of lagged RD).6 Our primary measure of RD is the cross-sectional standard deviation of firm returns for the largest 80% of NYSE/AMEX individual common stocks, based on market capitalization.

We find that RD provides reliable, incremental information about a firm’s future volatility. We find consistent results for a limited sample of Japanese and UK stock returns. Further, our results suggest that RD contains more incremental information for future firm-level volatility than do lagged market-level return shocks.

Our study also investigates whether RD contains incremental information for the future traditional volatility of market-level stock returns and various disaggregate stock portfolio returns. We find that the volatility information from RD is pervasive and is not appreciably related to a firm’s size, industry, or market-beta. Our findings at the portfolio-level may suggest applications of volatility timing in asset allocation (see, e.g., Busse, 1999; Fleming et al., 2001).

4 Changing industrial composition that accompanies the economic development process may also induce a relation between market-level volatility and return dispersion. As noted by Bekaert and Harvey (2000), “As an economy becomes more developed and the stock market more mature, there is often less reliance on one particular sector (the correlation between stocks decreases), which increases the cross-sectional standard deviation” (p. 581). This explanation is more relevant for emerging markets in transition and seems unlikely to be important for our study.

5 Veronesi (1999) argues that uncertainty about the stock market’s dividend growth rate may be positively associated with volatility. Shalen (1993) and Harris and Raviv (1993) suggest that a higher dispersion-in-beliefs is likely to be associated with higher turnover and higher return volatility. Also, see our discussion of other related RD literature in Section 2.1.

6 The distinction between our RD term and CSV term is subtle. By RD, we refer to the simple cross-sectional standard deviation of returns about an equally-weighted portfolio return. By CSV, we refer to a conditional cross-sectional volatility that is formed from a time-series model of lagged RD observations.
To examine robustness and assist with interpretation, we also evaluate alternate sample periods and alternate RD measures. We find that our volatility results are consistent for our primary sample period of 1988 to 1996, our pre-evaluation sample period of 1985 to 1987, and our post-evaluation sample period of 1997–1999. Next, we find that alternate RD measures, such as the dispersion of industry portfolio returns about the market return and the dispersion of size-based portfolio returns about the market return, provide similar information as our primary firm-level RD. However, among the alternate RDs that we evaluate, our primary firm-level RD is a simple, broad RD measure that generally provides the best quality information about the future stock volatility. Accordingly, for brevity and focus, we report details on the alternate RD measures in Appendix A.

In Section 2, we further discuss the existing literature on return dispersion and firm-level volatility. Section 3 defines the primary RD measure in this paper and explains how we form our conditional cross-sectional volatility. In Section 4, we present our main empirical volatility specifications. Section 5 presents the data and Section 6 reports the results from the estimation of the specifications described in Section 4. Finally, in Section 7, we report on the relation between cross-sectional return dispersion, stock turnover, and macroeconomic news releases. Section 8 concludes.

2. Related literature

2.1. Return dispersion

Studies that use or analyze dispersion in monthly stock returns include Loungani et al. (1990), Christie and Huang (1994), Stivers (2003), and the aforementioned Bekaert and Harvey (1997, 2000). Loungani, Rush, and Tave find that return dispersion leads unemployment which suggests that dispersion may be related to transitions in the economy. Christie and Huang study monthly return dispersion and find that dispersion tends to be higher during recessions and positively co-varies with the yield spread between high and low rated corporate bonds. Stivers finds that monthly dispersion in large-firm returns contains reliable information about the future volatility of monthly market-level returns over the 1927–1995 sample period.7

Connolly and Stivers (2003) use weekly cross-sectional RD in their study of momentum and reversals in stock-index returns. They find that: (1) unexpectedly high RD in week \( t \) is associated with substantial momentum in consecutive weekly equity-index returns from weeks \( t - 1 \) to \( t \), (2) unexpectedly low RD in week \( t \) is associated with substantial reversals in consecutive weekly equity-index returns from weeks \( t - 1 \) to \( t \), and (3) the unexpected RD is substantially positively correlated with the unexpected stock turnover. If the RD shock is positively related to the dispersion-in-beliefs about the market

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7 In contrast with our study, Stivers examines: (1) the monthly return horizon only (rather than this study’s daily horizon), (2) market-level return volatility only (rather than this study’s focus on the volatility of firm-level returns and disaggregate portfolio returns), (3) a single large-firm RD series only (rather than the multiple measures of RD in this study), and (4) return time-series data only (whereas turnover is also studied in this paper).
information signal, then the momentum and reversals could follow from frameworks such as Wang’s (1994).

In this study, we are interested in RD in daily returns. To our knowledge, only a few prior studies have used return dispersion at the daily horizon and none of these papers are volatility studies that are directly comparable to this paper. Bessembinder et al. (1996) study the determinants of trading volume and document a positive correlation between their return dispersion measure and detrended aggregate trading volume. Their interpretation is that their dispersion measure reflects firm-specific information flows. Their findings are related to results that we present in Section 7, so we further discuss the similarities and differences there. Both Christie and Huang (1995) and Chang et al. (2000) use dispersion to evaluate the notion of herding in stock returns during periods of extreme market movements. Neither paper finds evidence of herding in the US markets.

2.2. Other firm-level volatility literature

The firm-level analysis in our paper adds to the growing empirical literature on firm-level volatility. While Campbell et al. (2001) (CLMX) observe that, “there is surprisingly little empirical research on volatility at the level of the industry or firm” (p. 2), recent work indicates a growing interest in this area. CLMX note that firm-level volatility is important in a number of settings including portfolio diversification issues, firm-level option pricing, and event studies. In their paper, CLMX characterize broad trends in aggregate firm-level volatility rather than focusing on specific individual firms. They analyze monthly measures of aggregate market-level, industry-level, and firm-level volatility. Over the 1962–1997 period, they find a noticeable increase in firm-level volatility relative to market volatility, but no upward trend in volatility at the market level. Thus, CLMX’s results indicate interesting differences between time-variation in firm-level volatility versus market-level volatility.

Connor et al. (in press) develop a return model in which time-varying volatility is driven by three components: one related to an asset pricing factor, another to a common asset-specific component, and yet another to an idiosyncratic asset-specific component. Their results suggest that monthly, firm-level return volatility has a large “common asset-specific” component. They note that these patterns in the data are not obvious features of existing asset pricing models: “A theoretical explanation for these observed patterns, whether a rational-choice-based theory or a behavioral theory, would be a notable contribution” (p. 16). In our view, the intuition behind their “common asset-specific component” is similar to the intuition behind our “cross-firm volatility” in this study. However, their factor representation is quite different from our approach and their study examines monthly returns while our focus is on daily returns.

Other studies have evaluated whether market volatility provides incremental information when modeling the conditional volatility of individual firms (Engle and Lee, 1993) or disaggregated portfolios (Schwert and Seguin, 1990). Engle and Lee examine the stock returns of 14 large-capitalization stocks and find that the market return provides incremental information about individual firm conditional volatility beyond the information in lagged-own firm return shocks. Schwert and Seguin examine time-varying volatility in size-sorted portfolios and find evidence of a common-factor in volatility for these portfolios.
Malkiel and Xu (2001) present important evidence that increasing firm-level volatility in the 1980s and 1990s can be traced back to the idiosyncratic volatility component. Their study indicates that the extent of the increase might be systematically related to the extent of institutional ownership of the firm and firm growth characteristics.

Bekaert and Wu (2000) develop a general empirical framework in which asymmetries can exist at the market and/or firm level. Using Japanese firm-level data aggregated into portfolios, they find that that the volatility asymmetry at the firm level may be due to covariance asymmetry. Simply put, in settings where returns are negative, the conditional covariance between market and firm returns is such that the volatility feedback effect is very strong, and this is the source of the oft-noted volatility asymmetry. In this respect, their work contrasts with earlier studies that focused on modeling asymmetry in conditional betas (see Braun et al., 1995 for a prominent example). Other recent firm-level volatility studies that have focused on understanding asymmetries in conditional volatility relations include Cheung and Ng (1992), and Duffee (1995, 2002a,b).

3. Return dispersion and conditional cross-sectional volatility

3.1. Cross-sectional return dispersion

In this section, we define our primary RD measure and explain how we use the RD time-series to form a conditional cross-sectional volatility. Our primary measure of cross-sectional dispersion is the RD of firm-level returns about the market return, defined as:

$$RD_{CF(mkt),t} = \left[ \frac{1}{n-1} \sum_{i=1}^{n} (R_{i,t} - R_{mkt,t})^2 \right]^{1/2}$$

where $n$ is the number of firms in the portfolio, $R_{i,t}$ is the return of individual firm $i$, and $R_{mkt,t}$ is the aggregate stock market return. The first subscript on the RD variable denotes which stock returns are dispersed about which portfolio return, here it is cross-firm (CF) return dispersion about the market return (mkt) or CF(mkt). We note that the market-level return is an equally-weighted portfolio return. We make this choice so that one can think of the RD variable as a cross-sectional standard deviation where each firm return is treated as an equal observation.

A second reason for using equally-weighted portfolio returns is that this choice facilitates a statistical decomposition of RD. Specifically, firm-level dispersion about the market return can be decomposed into: (1) the dispersion of firm returns about disaggregate portfolios, where the portfolios are formed by grouping firms based on some firm characteristic; and (2) the dispersion of the disaggregate portfolio returns about the market return. For example, it might prove worthwhile to decompose our primary $RD_{CF(mkt),t}$ into industry-level RD and the remaining firm idiosyncratic RD. Dispersion across industry returns might provide better information about the volatility of the underlying common factors than does our broad-market firm RD. If so, and if the volatility information in RD is attributed to the persistent volatility of multiple common factors, then an industry-level dispersion might subsume the information in our primary $RD_{CF(mkt),t}$ from (1).
In our subsequent empirical work, we do examine several alternate measures of cross-sectional RD (such as the dispersion of industry-level returns about the market and the dispersion of size-based portfolio returns about the market return). However, among the alternate RDs that we evaluate, our primary firm-level RD is a simple and broad RD measure that generally provides the best quality information about future stock volatility. Accordingly, for brevity and focus, we report details about the statistical decomposition of firm-level RD in Appendix A.

3.2. Construction of conditional cross-sectional variance

The primary objective of this study is to examine whether RD provides reliable incremental information about the future traditional volatility of firm-level and portfolio-level stock returns. Accordingly, we need a time-series model to form an expected RD, or conditional cross-sectional variance. So that our conditional cross-sectional variance (CSV) will be analogous to the traditional conditional variance of portfolio-level and firm-level returns, we define the CSV to be equal to the expected value of the squared RD, given the past RD observations. Our primary CSV is based on our broad firm-level RD, that is calculated from the largest 80% of the NYSE/AMEX stocks (see Section 5.2).

Our procedure is as follows. First, we square the raw RD and then take the natural log of the RD² (to reduce skewness and more normalize the raw RD²). Then, we estimate an AR(10) on the log of RD², as follows:

\[
\ln(\text{RD}_t^2) = \psi_0 + \sum_{\tau=1}^{10} \psi_{\tau} \ln(\text{RD}_{t-\tau}^2) + \nu_t
\]

where \(\nu_t\) is the residual and the \(\psi\)'s are estimated coefficients. Next, we define an expected \(\ln(\text{RD}_t^2)\) from estimating (2) as follows:

\[
E[\ln(\text{RD}_t^2)] = \psi_0 + \sum_{\tau=1}^{10} \psi_{\tau} \ln(\text{RD}_{t-\tau}^2)
\]

Finally, we convert this \(E[\ln(\text{RD}_t^2)]\) back to an expected RD², as follows:

\[
V_{\text{CF}(\text{mkt}), t} = \exp\left[ E[\ln(\text{RD}_{\text{CF}(\text{mkt}), t}^2)] \right]
\]

Thus, the \(V_{\text{CF}(\text{mkt}), t}\) is a conditional cross-sectional variance (or conditionally expected RD²), formed from the past time-series of RD. This final step in (4) converts the units of the conditional cross-sectional variance back to “return-deviations squared,” which is directly comparable to the other traditional conditional variances.\(^8\) We choose ten lags

\(^8\) Note that this process of taking the log of the raw variable, performing the autoregressive model estimation, and then converting the fitted value back to the units of the raw variable follows from French et al. (1987). We feel that there is a nice symmetry between comparing the information about future volatility from the conditional volatilities from traditional GARCH models (that use the information in multiple lags of past return shocks in a time-series model) and a conditional cross-sectional volatility (that uses the information in multiple lags of RD in a time-series model).
when estimating (2) because, in practice, the ten lags adequately capture the time-series predictability of the variable and ten lags provides an even 2 weeks of lagged daily explanatory variables.

4. Empirical volatility specifications

4.1. Overview

In this section, we present our primary empirical specifications for estimating the traditional conditional volatility of daily stock returns. Our empirical innovation is the inclusion of an explanatory term that captures information in cross-firm return dispersion. Section 6 presents the corresponding empirical results.

Section 4.2 presents our primary model of conditional firm-level volatility. Three distinct explanatory components appear in each firm’s conditional variance equation: (1) the conditional variance of the respective firm’s idiosyncratic volatility (estimated solely from lagged idiosyncratic return shocks); (2) the conditional market-level variance (estimated solely from lagged market-level return shocks), and (3) the conditional cross-sectional variance (estimated from the past cross-firm return dispersion per Section 3.2). The model’s purpose is to evaluate whether past RD contains reliable information about the conditional volatility of firm returns, beyond the information contained in the past idiosyncratic return shocks and market-level return shocks. We discuss alternate specifications that could serve the same purpose in Appendix B.

Section 4.3 presents our primary model for the conditional volatility of portfolio-level stock returns. The portfolio-level model includes two explanatory terms; a portfolio-level conditional variance (estimated solely from the lagged return shocks from the respective portfolio) and the conditional cross-sectional variance (estimated from the past cross-firm RD per Section 3.2). We analyze aggregate market-level stock returns and industry, size-based, and market-beta-based stock portfolio returns. The purpose of the portfolio-level model is to evaluate whether past cross-firm RD contains reliable information about the conditional volatility of portfolio-level returns, beyond the information contained in the past portfolio-level return shocks.

For our estimation of the volatility specifications in this section, we estimate the conditional mean and variance equations simultaneously by maximum likelihood estimation using a likelihood function with a conditional normal density. We acknowledge that this conditional density is likely to be misspecified since even standardized return residuals are likely to exhibit excess kurtosis and (possibly) skewness. We use the conditional normal density for the following reasons. First, it is a well-known and widely used standard. Second, under straightforward regularity conditions, Bollerslev and Wooldridge (1992) show that a conditional normal likelihood function will provide consistent parameter estimates even if the standardized residuals do not exhibit a normal distribution. Third, our primary evaluation period is 1988–1996, which omits the October 1987 crash where deviations from conditional normality are the greatest. Finally, to foreshadow our results, we find that RD contains important information about subsequent volatility while studying: (1) hundreds of firm returns, (2) the equity markets of three
different countries, and (3) three alternate sample periods. The breadth of our findings suggests that it is unlikely that our conclusions would be significantly different if we used alternate densities. Nevertheless, in robustness testing reported in Appendix B, we also examine return densities that allow for excess kurtosis and find essentially identical results.

4.2. Conditional firm-level stock volatility: IMCS model

To examine the incremental information content in RD for future firm-level volatility, our primary specification is:

\[
R_{i,t} = \phi_0 + \phi_1 R_{i,t-1} + \phi_2 R_{\text{Mkt},t-1} + \epsilon_{i,t} \\
V_{i,t} = \phi_3 + \phi_4 V_{i,t}^{\text{Id}} + \phi_5 V_{\text{Mkt},t}^U + \phi_6 V_{\text{CF} \text{(mkt)},t}
\]  

(5)  

(6)

where \(R_{i,t}\) is the daily return of the individual firm, \(R_{\text{Mkt},t}\) is the daily return of our broad-market portfolio, \(\epsilon_{i,t}\) is the firm return residual, \(V_{i,t}^{\text{Id}}\) is the conditional variance of \(\epsilon_{i,t}\) to be estimated from the system of (5) and (6), \(V_{\text{Mkt},t}^U\) is the conditional variance of the firm’s idiosyncratic return component obtained from estimating the system given by (7) and (8) below, \(V_{\text{Mkt},t}^U\) is the market’s univariate conditional variance obtained from estimating the system given by (9) and (10) below, and \(V_{\text{CF} \text{(mkt)},t}^{\text{CF}}\) is the conditional cross-firm variance obtained from the estimation given by (2)-(4). The \(\phi\)’s are coefficients to be estimated. We refer to this model as our “idiosyncratic + market + cross-sectional model” or IMCS model.

To obtain the “idiosyncratic conditional variance” term in (6) above, \(V_{i,t}^{\text{Id}}\), we estimate the following model for each firm:

\[
R_{i,t} = \alpha_0 + \alpha_1 R_{\text{Mkt},t} + \alpha_2 R_{i,t-1} + \alpha_3 R_{\text{Mkt},t-1} + \eta_{i,t} \\
V_{i,t}^{\text{Id}} = \alpha_4 + (\alpha_5 + \alpha_6 D_{t-1}) \eta_{i,t-1}^2 + \alpha_7 V_{i,t-1}^{\text{Id}}
\]  

(7)  

(8)

where \(V_{i,t}^{\text{Id}}\) is the conditional variance of the firm’s idiosyncratic return component \(\eta_{i,t}\), the \(\alpha\)’s are coefficients to be estimated, and other terms are as defined before. By including the contemporaneous market return term in the conditional mean equation, the residual of (7) may be interpreted as an idiosyncratic return shock from a market-model perspective. The superscript \(\text{Id}\) indicates the idiosyncratic conditional variance.

To obtain the “univariate market-level variance” term in (6) above, \(V_{\text{Mkt},t}^U\), we estimate the following asymmetric GARCH(1,1) model.\(^9\) By univariate, we mean a conditional volatility model that uses only the series of lagged market-return shocks as explanatory variables.

\[
R_{\text{Mkt},t} = \gamma_0 + \gamma_1 R_{\text{Mkt},t-1} + \epsilon_{j,t} \\
V_{\text{Mkt},t}^U = \gamma_3 + (\gamma_4 + \gamma_5 D_{t-1}^-) \epsilon_{\text{Mkt},t-1}^2 + \gamma_6 V_{\text{Mkt},t-1}^U
\]  

(9)  

(10)

\(^9\) Thus, our IMCS model assumes that the conditional volatility of the market returns is weakly exogenous to any single individual firm return (in the statistical sense of Engle et al., 1983). We follow Engle and Lee (1993) in this respect.
where $R_{Mkt,t}$ is the daily return of our market portfolio Mkt, $\varepsilon_{Mkt,t}$ is the return residual, $V^U_{Mkt,t}$ is the conditional return variance, and $D_{t-1}^-$ is a dummy variable that equals 1 if $\varepsilon_{Mkt,t-1}$ is negative and is 0 otherwise. The superscript U for the conditional variance denotes that it is a univariate conditional volatility. The $\gamma$'s are coefficients to be estimated.

The volatility process in (10) is the asymmetric GARCH(1,1) variation proposed by Glosten et al. (1993). We also estimate this GJR asymmetric GARCH model for each firm’s stock return in order to evaluate the gain from the additional explanatory terms in our IMCS model. We use the GJR model for our primary univariate model of conditional volatility for the following reasons. First, this specification is parsimonious and widely used. Second, Engle and Ng (1993) compare a number of univariate GARCH models and find that the GJR model is among the best parametric GARCH models. Third, in our sample, we find that the GJR asymmetry is important for both market-level returns and a substantial proportion of the individual firms.

Our IMCS model has several attractive features. First, it is parsimonious with relatively few estimated parameters (as compared to a large-scale multivariate GARCH system). Second, in regards to the information about a firm’s conditional return volatility, the model allows different decay structures for the lagged market-level return shocks, idiosyncratic return shocks, and cross-firm return dispersion. Third, our approach ensures that the market-level conditional volatility and the conditional cross-sectional volatility are identical explanatory variables in (6) for every firm’s conditional volatility.10 Fourth, in our experience, our IMCS model typically converges quickly during maximum likelihood estimation. Finally, since our work is an initial evaluation of the information content of daily cross-sectional volatility, we feel a simple approach (such as our IMCS model) is appropriate.

We acknowledge a disadvantage to our approach is that it requires a first-stage estimation of $V^U_{I,t}$, $V^U_{Mkt,t}$, and $V^U_{CF(mkt),t}$ for use in our primary IMCS model. This introduces a possible error-in-variables concern. However, in our view, this concern seems highly unlikely to affect our primary inferences, because of: (1) the very high statistical significance of the explanatory variables in the first-stage estimations (so the errors-in-variables are small), and (2) the pervasiveness of our findings.

We also acknowledge that it is possible that lagged cross-product terms (such as the product of the lagged market-return shock and the lagged idiosyncratic firm-return shock) may have an incremental explanatory role for the expected firm volatility. If so, then cross-product terms should be included as an additional explanatory terms in Eq. (6). However, in additional testing, we find that lagged cross-product terms appear to add little explanatory power to a firm’s conditional volatility.11

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10 An alternate approach, for example, would be to try and simultaneously estimate a conditional market volatility, cross-firm volatility, and idiosyncratic volatility for each firm in a trivariate system. However, ensuring convergence for over 1000 separate simultaneous trivariate systems (one system per firm in our sample) would be onerous and the estimated market-level and cross-firm volatilities could be appreciably different across firms.

11 Specifically, we estimate a conditional volatility model that includes the product of the lagged market-return shock and the firm-return shock as an explanatory variable in a firm’s conditional variance equation, along with the market and idiosyncratic components. For this model, the cross-term is a statistically significant explanatory variable for only about 15% of the firms at a 5% $p$-value.
4.3. Conditional portfolio-level stock volatility

For portfolio-level returns, our primary model for the conditional mean and variance of portfolio $k$’s return is given by:

$$ R_{k,t} = \kappa_0 + \kappa_1 R_{k,t-1} + \epsilon_{k,t} \tag{11} $$

$$ V_{k,t} = \kappa_2 + \kappa_3 V_{k,t}^{U} + \kappa_4 V_{CF(mkt),t} \tag{12} $$

where $R_{k,t}$ is the daily return of the respective portfolio $k$; $\epsilon_{k,t}$ is the portfolio return residual; $V_{k,t}$ is the conditional variance for portfolio $k$ to be estimated; $V_{k,t}^{U}$ is the univariate conditional variance of portfolio $k$ obtained from estimating the GJR-GARCH system given by (9) and (10) but with the return of portfolio $k$ replacing the market-level return, and $V_{CF(mkt),t}$ is the conditional cross-firm variance obtained from the estimation given by (2)–(4). The $\kappa$’s are coefficients to be estimated.

Here, for the portfolio returns, we do not include the separate market-level conditional variance as an explanatory term in the portfolio’s conditional variance equation. We make this choice because we examine a wide variety of portfolio returns, including the aggregate market portfolio. So, of course in this case, the univariate portfolio-level volatility would be the same as the univariate market-level volatility. Even the disaggregate portfolios that we examine are substantially correlated with the market, so inclusion of a separate univariate market-level conditional variance would be largely redundant and would be hard to distinguish between the univariate portfolio-level conditional variance.

5. Data description and variable construction

5.1. US stock returns

5.1.1. Individual firm stock returns

Our empirical analysis examines daily US stock return data from the CRSP return files over the January 1985 through December 1999 period. In our initial empirical work, we focus on the 1988–1996 period for several reasons. First, this choice avoids distortions related to the October 1987 market crash. Second, this period is sizable ($n = 2274$ daily observations), includes a recession, and has both bull and bear market trends. A sample period of at least a few years is desired when estimating GARCH coefficients (see, e.g., Noh et al., 1994), however, we also desire to limit the sample length to minimize the likelihood of parameter instability. Third, by leaving the 1985–1987 and 1997–1999 periods for later analysis, this approach allows us to also analyze pre- and post-period samples for comparison and to examine robustness.

For our principal work on firm-level conditional volatility, we examine all NYSE firms that have a complete set of daily equity returns over the 1985–1996 period, a total of 1081 firms. We divide this group of firms into two size-based sets, using a firm’s average equity market capitalization over the sample period. This procedure leaves us with set of large NYSE firms ($n = 540$ firms) and a set of smaller NYSE firms ($n = 541$ firms). We only report the results for the set of large firms in our tables because: (1) we are interested in the volatility
processes of large, economically important firms, and (2) market frictions and illiquidity should have a minimal impact on the daily returns dynamics of these large firms. We also analyze the set of small firms and report small-firm results in the text for comparison. Table 1, Panel A, presents summary statistics for the firm characteristics for our sample of NYSE stocks.

5.1.2. Portfolio-level returns

Our work also examines the conditional volatility of daily stock returns for a broad-market stock portfolio and for various disaggregate stock portfolios. Aspects of our work analyze disaggregate stock portfolios formed by sorting firms on industry, market capitalization (size), and a firm’s market-beta.

For our analysis of firm-level conditional volatilities, our broad market-level stock portfolio is the equally-weighted average return of the largest 80% of NYSE/AMEX firms. We do this for consistency, since this portfolio includes the same set of firms used to

Table 1
Descriptive statistics for firm stock returns and return dispersions

Panel A: Firm return characteristics

<table>
<thead>
<tr>
<th>Mean return%</th>
<th>Uncond. St. Dev.%</th>
<th>Correlation Ri to Rmkt</th>
<th>Correlation Ri² to Rmkt²</th>
<th>Correlation Ri² to Rmkt²</th>
<th>Firm’s market-beta</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.070</td>
<td>2.02</td>
<td>0.352</td>
<td>0.414</td>
<td>0.088</td>
</tr>
<tr>
<td>10th Pct.</td>
<td>0.031</td>
<td>1.14</td>
<td>0.183</td>
<td>0.086</td>
<td>0.023</td>
</tr>
<tr>
<td>25th Pct.</td>
<td>0.046</td>
<td>1.43</td>
<td>0.272</td>
<td>0.189</td>
<td>0.05</td>
</tr>
<tr>
<td>Median</td>
<td>0.065</td>
<td>1.80</td>
<td>0.363</td>
<td>0.389</td>
<td>0.084</td>
</tr>
<tr>
<td>75th Pct.</td>
<td>0.088</td>
<td>2.35</td>
<td>0.447</td>
<td>0.633</td>
<td>0.124</td>
</tr>
<tr>
<td>90th Pct.</td>
<td>0.119</td>
<td>3.16</td>
<td>0.504</td>
<td>0.791</td>
<td>0.158</td>
</tr>
</tbody>
</table>

Panel B: Cross-firm return dispersions for size-based portfolios

<table>
<thead>
<tr>
<th>RD_{CF(mkt)}</th>
<th>RD_{i0}</th>
<th>RD_{i1}</th>
<th>RD_{i2}</th>
<th>RD_{i3}</th>
<th>RD_{i4}</th>
<th>RD_{i5}</th>
<th>RD_{i6}</th>
<th>RD_{i7}</th>
<th>RD_{i8}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.16</td>
<td>1.44</td>
<td>1.67</td>
<td>1.84</td>
<td>1.97</td>
<td>2.12</td>
<td>2.28</td>
<td>2.48</td>
<td>2.83</td>
</tr>
<tr>
<td>10th Pct.</td>
<td>1.83</td>
<td>1.11</td>
<td>1.31</td>
<td>1.47</td>
<td>1.59</td>
<td>1.69</td>
<td>1.81</td>
<td>1.95</td>
<td>2.18</td>
</tr>
<tr>
<td>25th Pct.</td>
<td>1.94</td>
<td>1.23</td>
<td>1.43</td>
<td>1.6</td>
<td>1.72</td>
<td>1.83</td>
<td>1.95</td>
<td>2.12</td>
<td>2.39</td>
</tr>
<tr>
<td>Median</td>
<td>2.08</td>
<td>1.39</td>
<td>1.62</td>
<td>1.78</td>
<td>1.9</td>
<td>2.02</td>
<td>2.17</td>
<td>2.36</td>
<td>2.67</td>
</tr>
<tr>
<td>75th Pct.</td>
<td>2.29</td>
<td>1.58</td>
<td>1.83</td>
<td>2.0</td>
<td>2.12</td>
<td>2.26</td>
<td>2.46</td>
<td>2.68</td>
<td>3.11</td>
</tr>
<tr>
<td>90th Pct.</td>
<td>2.58</td>
<td>1.80</td>
<td>2.07</td>
<td>2.28</td>
<td>2.42</td>
<td>2.65</td>
<td>2.9</td>
<td>3.13</td>
<td>3.66</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.34</td>
<td>0.32</td>
<td>0.35</td>
<td>0.38</td>
<td>0.39</td>
<td>0.48</td>
<td>0.50</td>
<td>0.54</td>
<td>0.65</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.68</td>
<td>0.43</td>
<td>0.47</td>
<td>0.34</td>
<td>0.37</td>
<td>0.35</td>
<td>0.41</td>
<td>0.44</td>
<td>0.54</td>
</tr>
<tr>
<td>Corr. w/RD_{CF(mkt)}</td>
<td>1.00</td>
<td>0.54</td>
<td>0.61</td>
<td>0.61</td>
<td>0.65</td>
<td>0.70</td>
<td>0.72</td>
<td>0.72</td>
<td>0.78</td>
</tr>
</tbody>
</table>

This table reports basic descriptive statistics for the daily individual firm stock returns and the daily return dispersions (RD) in this study. Panel A reports summary statistics for the firm stock returns for our sample of 1081 NYSE firms. For the correlations and market-beta, R_{mkt} is the equally-weighted portfolio return of the largest 80% of NYSE/AMEX firms (see Section 5.1.2), R_i is individual firm i, and RD_{CF(mkt)} is our broad cross-firm RD measure. Panel B reports summary statistics for cross-firm RDs about size-based portfolio returns for the firms that comprise the respective portfolio. We report on our broad-market RD_{CF(mkt)} (formed from the largest 80% of NYSE/AMEX firms) and RDs from the largest eight size-based, decile-portfolios. The RD_{i0} through RD_{i8} notation in the table is short hand for our RD_{i(portfolio)} notation as explained in Section 3.1, where i0 is the largest decile portfolio. All statistics are for the 1988–1996 period and all return statistics are reported in percentage form.
calculate our broad firm-level RD about the market return (see Section 3.1). For comparison, the correlation between this broad-market portfolio return and the CRSP value-weighted index portfolio is 0.924 over our primary 1988 to 1996 sample period.

We construct the size-based, decile-portfolios that are used in our empirical work as follows. For every trading day in our sample period, we include all NYSE and AMEX common stocks that have return, price, and shares outstanding available. We calculate each firm’s stock market capitalization and then sort firms based on their market capitalization. Then, we calculate daily, equally weighted, portfolio returns for each size decile and for the largest 80% of firms for our broad-market US portfolio.

We also analyze the daily returns of industry portfolios and beta-sorted portfolios. We postpone their description until we get to their results in Section 6 and Appendix A.

5.2. Firm-level return dispersion about the market return

We use individual firm returns to construct several daily RD measures, as given by (1). Our empirical work primarily focuses on a broad firm-level RD that is calculated from the largest 80% of the NYSE/AMEX stocks (based on the equity market capitalization of each stock). We choose not to include the smallest 20% of firms in our broad-market RD metric due to concerns that small-firm returns may generate RD variation that is unrelated to the market-wide environment. For example, high non-synchronous trading in small firm stocks or high idiosyncratic small-firm volatility could generate high RD that does not reflect the overall market environment. Fig. 1 displays our broad-market firm RD series graphically over our primary sample period of 1988–1996.

For comparison and to examine cross-sectional pervasiveness, we also calculate narrower firm-level RD measures that indicate the firm-level dispersion about specific size-based and industry portfolios. For example, \( \text{RDCF}(10) \) indicates the dispersion of the firms in the largest decile about the decile-ten portfolio return. In Table 1, Panel B, we present descriptive statistics for our broad-market RD and for portfolio-specific RDs for the eight largest size-based portfolios. The cross-sectional return dispersion decreases monotonically with firm size. For brevity, we report on firm dispersions about industry returns in Appendix A.

5.3. Conditional cross-sectional variance (CSV)

We calculate the CSV for various RD measures using the procedure in Section 3.2. Table 2 reports on nine different CSV series, our broad firm-level RD and size-based
firm RD’s for the eight largest size-based, decile-portfolios. The explanatory power of the model is substantial with most of the explanatory power captured by the first two RD lags. Our broad-market RD (formed from the largest 80% of NYSE/AMEX firms by market capitalization) exhibits the most time-series predictability with an $R^2$ of 54%. This suggests that our broad-market RD diversifies away some of the idiosyncratic dispersion that is evident in the RD from the decile-portfolios and that the common market-wide component of RD exhibits substantial autoregressive persistence. The explanatory power of (2) does not obviously vary with size across the decile portfolios.

Fig. 2 depicts both the CSV and the residual from estimating (2) for our broad-market RD series. First, note that the residual appears to be approximately white noise with essentially no autocorrelation or heteroskedasticity over time. Second, note the substantial time-series variation in the conditional cross-firm volatility.

Stivers (2003) shows that in a market-model framework, firm-level RD and the absolute market return should be correlated because the cross-firm dispersion in market-betas generates return dispersion in response to the market-return shock. Since RD and the absolute market return are correlated, it may be difficult to separate the volatility information in RD from past market return shocks. In our sample, we find that the correlation between the conditional market-level variance (from an asymmetric GARCH(1,1) model) and our CSV (from our broad firm-level RD) is modest at 0.54. Thus, this issue is not likely to be a major concern for our study.
5.4. Other data

5.4.1. Stock turnover data

In Section 7, we examine the relation between stock turnover and RD. The turnover is constructed from the daily trading volume and shares outstanding from CRSP, where turnover equals: (shares traded)/(shares outstanding). We evaluate the average turnover of the firms that make-up our broad-market portfolio (the largest 80% of NYSE/AMEX firms).

5.4.2. Japanese and United Kingdom (UK) stock return data

We also take some initial steps toward establishing the generality of our findings across other markets. To that end, we study the conditional variances of daily stock returns for 20 large-cap firms from Japan and 20 large-cap firms from the UK. From DataStream International, we select the 20 largest non-bank firms that have daily returns over our entire sample (measured by their 1996 stock market capitalization). The sample period is 1988–1996.

To estimate the return dispersion for each country, we collect individual firm returns for the firms that comprise the Nikkei-225 for Japan and the FTSE-100 for the U.K. For each market, we calculate RD by applying Eq. (1) to all available individual firm returns that comprise each respective index. For an aggregate market return in each country, we use the mean return of the available Nikkei-225 and FTSE-100 firm stock returns.

5.4.3. Macroeconomic news announcements

Finally, it is well known that macroeconomic-news releases tend to be associated with higher traditional market-level volatility. However, after controlling for the absolute

Table 2
Conditional cross-sectional volatilities

<table>
<thead>
<tr>
<th>Firm RD from:</th>
<th>$\psi_1$</th>
<th>$\psi_2$</th>
<th>Sum: $\psi_3$ to $\psi_{10}$</th>
<th>$R^2$</th>
<th>$\sigma_{CSV}$</th>
<th>$\rho_{\text{mkt},i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Broad Market</td>
<td>0.361 (14.21)</td>
<td>0.168 (6.72)</td>
<td>0.363</td>
<td>0.544</td>
<td>1.16</td>
<td>1.00</td>
</tr>
<tr>
<td>Decile 10</td>
<td>0.302 (10.78)</td>
<td>0.139 (4.78)</td>
<td>0.366</td>
<td>0.329</td>
<td>0.49</td>
<td>0.64</td>
</tr>
<tr>
<td>Decile 9</td>
<td>0.303 (11.47)</td>
<td>0.139 (5.45)</td>
<td>0.372</td>
<td>0.345</td>
<td>0.67</td>
<td>0.71</td>
</tr>
<tr>
<td>Decile 8</td>
<td>0.237 (10.04)</td>
<td>0.101 (4.69)</td>
<td>0.431</td>
<td>0.245</td>
<td>0.64</td>
<td>0.78</td>
</tr>
<tr>
<td>Decile 7</td>
<td>0.231 (9.62)</td>
<td>0.161 (8.18)</td>
<td>0.386</td>
<td>0.270</td>
<td>0.76</td>
<td>0.80</td>
</tr>
<tr>
<td>Decile 6</td>
<td>0.186 (7.37)</td>
<td>0.122 (5.60)</td>
<td>0.480</td>
<td>0.264</td>
<td>1.03</td>
<td>0.89</td>
</tr>
<tr>
<td>Decile 5</td>
<td>0.200 (8.38)</td>
<td>0.140 (6.69)</td>
<td>0.490</td>
<td>0.329</td>
<td>1.33</td>
<td>0.89</td>
</tr>
<tr>
<td>Decile 4</td>
<td>0.242 (10.58)</td>
<td>0.119 (5.68)</td>
<td>0.452</td>
<td>0.319</td>
<td>1.52</td>
<td>0.88</td>
</tr>
<tr>
<td>Decile 3</td>
<td>0.212 (9.10)</td>
<td>0.142 (6.64)</td>
<td>0.529</td>
<td>0.448</td>
<td>2.58</td>
<td>0.89</td>
</tr>
</tbody>
</table>

This table reports on estimating the conditional cross-sectional volatilities; see Eqs. (2)–(4), Section 3.2. Rows one through nine report results for firm-level, size-based RDs; specifically our broad-market RD (formed from the largest 80% of NYSE/AMEX firms) and the largest eight size-based, decile-portfolios (where 10 is the largest). Columns two and three report the estimated coefficient on the first two lags in the AR10 model (Eq. (2)) with t-statistics in parentheses, calculated with robust standard errors per the Newey and West (1987) method. Column four reports the sum of the estimated coefficients for lags three through ten. Column five reports the $R$-squared from estimating (2). Column six reports the time-series standard deviation, $\sigma_{CSV}$, of the row’s conditional cross-sectional variance (CSV). Finally, column seven reports the correlation between the conditional CSV using row $i$’s RD and the conditional CSV using our broad-market RD. The sample period is 1988–1996.
market return, it is not known whether cross-firm return dispersion tends to be higher or lower on these news days. For example, if the news tends to resolve uncertainty about the economic state and make the market signal less ambiguous, then the news-release days might tend to have relatively low RD.

To explore this issue, we obtain economic news announcement data from MMS International to investigate whether return dispersion is different on macroeconomic-news release days. We examine the Producer Price Index and unemployment announcements because they are associated with a significant contemporaneous increase in the traditional volatility of market-level returns and because of their use in Jones et al. (1998).

6. Cross-firm return dispersion and the future volatility of stock returns: main empirical results

6.1. Conditional stock volatility: univariate model

We begin by estimating the asymmetric GARCH(1,1) model, given by (9) and (10) in Section 4.2, on the return series for each of the 540 individual large US firms and our broad-market stock portfolio. The results depict the volatility behavior using a well-known model and provide a benchmark for comparison to later results. Table 3 summarizes the

---

Fig. 2. Conditional cross-firm volatility and the cross-firm volatility shock. This figure display the timeseries of conditional cross-firm volatilities (the upper series, scale on left axis) formed per Section 3.2, and the cross-firm volatility shock (the lower series, scale on right axis) as indicated by the residual from estimating Eq. (2). The conditional cross-firm volatility is formed from our broad firm-level RD about the market return, which uses the largest 80% of NYSE/AMEX stocks. The sample period is 1988–1996.
estimates. Given the large number of individual firm return series, we elect to report the
distribution of the estimated GARCH coefficients and the number of estimated coefficients
that are positive (or negative) and significant at the 10% significance level or better. The
\( p \)-values are estimated with standard errors that are robust to departures from conditional

We find standard GARCH behavior for the vast majority of firms. For the large
individual firms (Table 3, Panel A), the median \( \alpha_5 \) on the \( V_{i,t-1} \) term is 0.887, and 75% of
the estimated \( \alpha_5 \)'s are greater than 0.749. The median \( \alpha_1 \) on the \( \varepsilon_{i,t-1}^2 \) term is 0.042, and
75% of the estimated \( \alpha_1 \)'s are greater than 0.021. The so-called leverage asymmetry is
reliably evident for only about one-third of the firms with a median estimated \( \alpha_2 \) on the
\( D_{i,t} \varepsilon_{i,t-1}^2 \) term of 0.032. The standard GARCH behavior is also evident for the market-
level stock return (Table 3, Panel B). The leverage asymmetry is evident and stronger for
the market return than for the typical firm.

6.2. Conditional firm-level stock volatility: IMCS model

Next, we report results for estimating our “idiosyncratic + market + cross-sectional” or
IMCS model of conditional firm-level volatility, as given by (5) and (6) in Section 4.2. Recall
that this model examines whether RD contains incremental information for a firm’s
future volatility, beyond the information contained in the firm’s conditional idiosyncratic
variance (formed from lagged idiosyn-cratic return shocks) and the conditional variance of
market-level returns (formed from lagged market-level return shocks).

Table 4 summarizes the results for our sample of 540 large NYSE firms. We find that
the RD term, \( V_{CF(mkt)} \), is positively and reliably related to the conditional firm-level

<table>
<thead>
<tr>
<th>( \gamma_4 ) on ( \varepsilon_{i,t-1}^2 )</th>
<th>( \gamma_5 ) on ( D_{t-1} \varepsilon_{i,t-1}^2 )</th>
<th>( \gamma_6 ) on ( V_{i,t-1}^U )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>0.042</td>
<td>0.032</td>
</tr>
<tr>
<td>25th Pct.</td>
<td>0.021</td>
<td>0.012</td>
</tr>
<tr>
<td>75th Pct.</td>
<td>0.079</td>
<td>0.059</td>
</tr>
<tr>
<td>Positive and sign.</td>
<td>260</td>
<td>152</td>
</tr>
<tr>
<td>Negative and sign.</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

This table reports results from estimating a GJR-GARCH(1,1) conditional volatility model on the daily stock
returns of each firm in our sample of 540 large NYSE firms. Eqs. (9) and (10) in Section 4.2 specify the model,
but with firm returns replacing the market returns. In the model, \( \varepsilon_{i,t} \) is the return residual of stock \( i \), \( D_{i,t} \) is a
dummy variable that equals one if the residual is negative, \( V_{i,t-1}^U \) is the lagged conditional variance for stock \( i \),
and the \( \gamma \)'s are estimated coefficients. Panel A reports on the daily returns of our sample of 540 large NYSE firms.
Row 4 (5) reports the number of the estimated coefficients that are positive (negative) and significant at a 10% \( p \)-
value level or better, based on Bollerslev-Wooldridge standard errors that are robust to departures from conditional
normality. In Panel B, we also report results for our broad-market portfolio return (the equally-
weighted portfolio return of the largest 80% of NYSE/AMEX firms). For Panel B, \( p \)-values for the estimated
coefficients are in parentheses. The sample period is 1988–1996.
variance for about 64% of the firms, based on $p$-values calculated from Bollerslev-Wooldridge standard errors. Inference based on a likelihood ratio test leads to similar conclusions. The median $\phi_6$ on the $V_{CF(mkt),t}$ term is 0.312 and 75% of the estimated $\phi_6$'s are greater than 0.141.

Next, the median $\phi_5$ coefficient for the univariate market-level conditional variance, $V_{Mkt,t}$, is 1.007 and the individual estimates are reliably positive for about 38% of the firms. This aspect of our findings seems broadly consistent with Engle and Lee (1993) and Schwert and Seguin (1990).13 Finally, the idiosyncratic explanatory term ($V_{Id}$) is quite important. The median of the estimated $\phi_4$ on $V_{Id}$ is 0.931 and the individual estimates are reliably positive for about 90% of the firms.

From the perspective of a market model, we note that if the true conditional variances for $V_{Id}$ and $V_{Mkt}$ were known and used in this estimation, then $\phi_4$ on $V_{Id}$ should be essentially equal to one, $\phi_5$ on $V_{Mkt}$ should be essentially equal to the squared market-beta for the firm, and $\phi_6$ on $V_{CF(mkt)}$ should be approximately zero (since the idiosyncratic and market-level terms are the only components in determining the firm’s return and variance in a market model). However, $V_{Id}$ and $V_{Mkt}$ are only estimates that rely upon the respective single series of lagged return shocks. Our point is that the cross-firm RD contains information for future firm-level volatility, beyond that contained in lagged market-level return shocks and lagged idiosyncratic return shocks for each firm. If the RD

---

13 Engle and Lee find that forecasts of individual firm volatility depend upon both market shocks and firm-specific shocks. Schwert and Seguin find a common market component in the heteroskedasticity of size-based portfolios returns.
term \((V_{CF(mkt)})\) contains reliable incremental information, then we would expect \(\phi_4\) to be less than one and/or the median \(\phi_5\) to be lower than the squared market-beta, on average (since some of the weight in determining the firm’s total conditional variance is being shifted to the RD term). Our results in Table 4 are consistent with this observation.

We also directly compare our IMCS model to the univariate GJR-GARCH model estimated on each firm return (see Eqs. (9) and (10) and Table 3) using a likelihood ratio test. This test indicates that our IMCS model statistically outperforms the GJR-GARCH model for about 60% of the firms at a 5% significance level.\(^{14}\)

Table 4 also reports summary statistics across the 540 firms for the time-series correlation between a firm’s conditional idiosyncratic variance and the conditional market-level variance (in column five) and the correlation between a firm’s conditional idiosyncratic variance and the conditional cross-sectional volatility (in column six). These correlations are quite modest with a median correlation of 0.106 for the former and 0.190 for the latter.

By comparison, the correlation between the conditional market-level variance \((V_{Mkt})\) and the conditional cross-firm volatility \((V_{CF(mkt)})\) is a more substantial 0.54. This sizable positive correlation suggests a sizable comovement between traditional market volatility and cross-firm RD, consistent with results in Campbell et al. (2001). Finally, these modest correlations between the three explanatory components in our IMCS model suggest reasonable power for distinguishing between the three explanatory terms and mitigate concerns about multicollinearity between these volatility series.

Finally, Table 4 reports on a measure of relative economic significance for each of the three explanatory terms in a firm’s conditional variance equation. We calculate a sensitivity ratio that provides information about the relative contribution of each explanatory term to the time-series variability in each firm’s total conditional variance. There is a sensitivity ratio for each explanatory term for each firm, where a relatively higher ratio suggests that the respective explanatory variable explains a relatively higher proportion of the time-series variability in a firm’s total conditional variance (as compared to explanatory terms with lower sensitivity numbers). Specifically, the sensitivity ratio for a given explanatory term for a given firm is defined as a ratio where: the numerator is “the estimated coefficient for the respective explanatory term times the difference between the 90th and 10th percentile of the time-series for the explanatory term,” and the denominator is “the difference between the 90th and 10th percentiles of the time-series for the respective firm’s conditional variance.”

These sensitivity ratios also indicate that the RD term is relatively more important than the market-level volatility when explaining conditional firm volatility. The median ratio for the RD term across the 540 firms is 0.305, compared to a median of only 0.120 for the conditional market-level volatility. Thus, both in terms of the statistical significance and in terms of our sensitivity ratios, the RD term appears more important than the traditional market-level volatility when modeling conditional firm volatility. The results from estimating our IMCS model on our sample’s 541 smaller NYSE firms are qualitatively comparable to those in Table 4. We find that the RD term is positively and reliably related

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\(^{14}\) Since the IMCS model approximately nests the GJR-GARCH model, it is expected that the IMCS model will perform better in terms of the likelihood function value. For this comparison, we are interested in whether the improvement tends to be statistically significant.
to the conditional firm-level volatility for about 52% of these smaller firms. This proportion is somewhat smaller than for the set of large firms, perhaps due to the higher idiosyncratic nature of the smaller firm returns.

We also estimate our primary IMCS model for a comparable large set of firms over the alternate periods of 1985–1987 and 1997–1999. In addition to checking for consistent results across alternate periods, evaluating the two 3-year alternate periods also examines whether our results are evident over shorter sample periods. Our firm-level results for these alternate periods are qualitatively comparable to the results in Table 4. For the 1997 to 1999 sample, we find that the RD term is reliably positive for about 67% of the firms. For the 1985 to 1987 sample, the RD term is reliably positive for about 38% of the firms (the lower proportion for the 1985 to 1987 period is related to the large robust standard errors attributed to the October 1987 market crash).

In addition, we examine the generality of our findings using firm-level stock returns from other countries. In Table 5, we report results from estimating our IMCS model on 20 large UK firms (Panel A) and 20 large Japanese firms (Panel B). We find that the RD term is a reliable explanatory term for the conditional volatility of 70% of the UK firms and 95% of the Japanese firms. Thus, the results from the Japan and UK reinforce our findings from the US market.

Table 5
UK and Japanese firm-level volatility results

<table>
<thead>
<tr>
<th></th>
<th>$\phi_4$ on $V_{i,t}^{id}$</th>
<th>$\phi_5$ on $V_{Mkt,t}^{U}$</th>
<th>$\phi_6$ on $V_{CF(mkt),t}$</th>
<th>Correlation ($V_{i,t}^{id}$, $V_{Mkt,t}^{U}$)</th>
<th>Correlation ($V_{i,t}^{id}$, $V_{CF(mkt),t}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: UK firm-level volatility results</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>0.959</td>
<td>0.752</td>
<td>0.916</td>
<td>0.228</td>
<td>0.366</td>
</tr>
<tr>
<td>25th Percentile</td>
<td>0.841</td>
<td>0.407</td>
<td>0.645</td>
<td>0.124</td>
<td>0.211</td>
</tr>
<tr>
<td>75th Percentile</td>
<td>1.024</td>
<td>1.192</td>
<td>1.322</td>
<td>0.350</td>
<td>0.443</td>
</tr>
<tr>
<td>Positive and sig.</td>
<td>20</td>
<td>10/7</td>
<td>14/12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Negative and sig.</td>
<td>0</td>
<td>0/0</td>
<td>0/0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity-Median</td>
<td>0.670</td>
<td>0.161</td>
<td>0.304</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity-25th Pct.</td>
<td>0.616</td>
<td>0.121</td>
<td>0.163</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity-75th Pct.</td>
<td>0.772</td>
<td>0.278</td>
<td>0.406</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Japanese firm-level volatility results</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median</td>
<td>0.785</td>
<td>0.371</td>
<td>1.598</td>
<td>0.283</td>
<td>0.497</td>
</tr>
<tr>
<td>25th Percentile</td>
<td>0.713</td>
<td>0.196</td>
<td>0.923</td>
<td>0.211</td>
<td>0.421</td>
</tr>
<tr>
<td>75th Percentile</td>
<td>0.838</td>
<td>0.436</td>
<td>1.778</td>
<td>0.356</td>
<td>0.562</td>
</tr>
<tr>
<td>Positive and sig.</td>
<td>19</td>
<td>15/15</td>
<td>19/17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Negative and sig.</td>
<td>0</td>
<td>0/0</td>
<td>0/0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity-Median</td>
<td>0.451</td>
<td>0.392</td>
<td>0.347</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity-25th Pct.</td>
<td>0.355</td>
<td>0.195</td>
<td>0.259</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity-75th Pct.</td>
<td>0.503</td>
<td>0.555</td>
<td>0.457</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table reports results from estimating the firm-level conditional volatility, given by Eqs. (5) and (6), on a sample of 20 large UK and 20 large Japanese firms. Panel A reports on the UK firms and Panel B reports on the Japanese firms. The model specification, all terms, and the table descriptions are the same as for Table 4. The return dispersion used to estimate the conditional cross-firm volatility is from the stock returns of the FTSE-100 (Nikkei 225) firms that are available in Datastream for the UK (Japan). The sample is comprised of daily returns over 1988–1996.
6.3. Conditional market-level stock volatility

Next, we investigate whether RD also contains information for the future volatility of the aggregate stock market. The econometric model is given by (11) and (12) in Section 4.3.

Table 6 reports US results, where the cross-sectional volatility is again formed from our broad firm-level RD. Row one reports results for our primary 1988 to 1996 sample period. We find that the RD term provides reliable incremental information about the future volatility of the index return with a p-value of 0.023 for the estimated $\kappa_4$ coefficient on the $V_{CF(mkt)}$ term. The sensitivity measure, as defined in Section 6.2, also indicates that RD provides important volatility information. The sensitivity for the $V_{CF(mkt)}$ term is 0.404. By comparison, the sensitivity to the univariate market-level $V_{Mkt}^U$ is 0.680. Next, rows two and three of Table 6 report results for the 1985 to 1987 and 1997 to 1999 periods, respectively. For these pre- and post-evaluation periods, the estimated coefficient on the $V_{CF(mkt)}$ term remains positive and statistically significant.

Next, we estimate the system given by (11) and (12) for market-level stock returns for the UK and Japan. The UK results are quite similar to those for the US in Table 6; the $t$-stat for the estimated $\kappa_4$ on the $V_{CF(mkt)}$ term is 2.77 and the $V_{CF(mkt)}$ term’s sensitivity is sizable at 0.31. For Japan, the estimated $\kappa_4$ for the $V_{CF(mkt)}$ term is positive but insignificant with a $t$-stat of 1.20. Taken collectively, the above results suggest that cross-firm RD contains information about the future volatility of market-level stock returns.

6.4. Variability across industries, firm size, and firm market-betas

We also investigate whether the relation between RD and future volatility varies with a firm’s industry, size, or market-beta. This supplementary investigation has three primary purposes. First, it serves to characterize further the breadth and nature of the RD-volatility relation. Second, it may contribute to a deeper understanding of the economics behind the information in RD. For example, if the RD-volatility relation is stronger and more reliable in portfolios of high-beta firms, then our findings may be related to systematic risk.

Table 6

<table>
<thead>
<tr>
<th>Sample period</th>
<th>$\kappa_3$ on $V_{Mkt}^U$</th>
<th>$\kappa_4$ on $V_{CF(mkt)}$</th>
<th>Sensitivity ratio $V_{Mkt}^U$</th>
<th>$V_{CF(mkt)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1988–1996</td>
<td>0.729 (4.13)</td>
<td>0.079 (2.27)</td>
<td>0.680</td>
<td>0.404</td>
</tr>
<tr>
<td>1985–1987</td>
<td>0.920 (3.63)</td>
<td>0.079 (1.84)</td>
<td>0.906</td>
<td>0.165</td>
</tr>
<tr>
<td>1997–1999</td>
<td>0.984 (5.69)</td>
<td>0.057 (2.16)</td>
<td>0.924</td>
<td>0.200</td>
</tr>
</tbody>
</table>

This table reports results from estimating the conditional market-level volatility model given by Eqs. (11) and (12) in Section 4.3. The market return is the return of the CRSP value-weighted index of NYSE/AMEX/NASDAQ stocks. The $\kappa$’s are estimated coefficients on the explanatory terms, where $\kappa_3$ is for the $V_{Mkt}^U$ term and $\kappa_4$ is for the $V_{CF(mkt)}$ term. The cross-sectional volatility term, $(V_{CF(mkt)})$, is formed from our broad firm-level RD about the market return. $V_{Mkt}^U$ is the conditional market-level volatility from a univariate GJR GARCH model. $t$-stats for the respective coefficients are in parentheses, calculated with robust standard errors in accordance with Bollerslev and Wooldridge (1992). The last two columns report the sensitivity ratios that provide information about the relative importance of each explanatory term in the conditional variance equation, see Section 6.2.
Alternatively, if the RD-volatility relation is stronger for small-firm portfolios, this might suggest a role for market frictions and delayed information incorporation in understanding our findings. Or, if the RD-volatility relation is strong for only a few industries, this would suggest a lack of generality and a potential link to specific industry characteristics such as intra-industry competition, transparency, or maturity.

6.4.1. Results across firm size

Table 7 presents the results for estimating our portfolio-level volatility model, Eqs. (11) and (12), on the returns of the eight largest size-based, decile-portfolios. We find that our broad firm level RD (the $V_{CF(mkt)}$ term) provides reliable incremental information for the future volatility for all eight portfolios. The sensitivity measures in the final column of the table for the $V_{CF(mkt)}$ term seem substantial. For comparison, Appendix A reports results on the relation between the volatility of each specific size-based portfolio and the corresponding portfolio-specific RD (the RD across the firms that comprise the respective size-based portfolio).

6.4.2. Results across firm market-betas

We also examine whether the strength of the RD-volatility relation varies with a firm’s market-beta. To do this, we analyze the conditional return volatility for portfolios of high, mid, and low beta stocks, as follows. First, we subdivide our sample of 1081 firms into 11 subsets of approximately 98 firms/subset, based on the first 3-digits of a firm’s CUSIP. Then, for each of the 11 subsets, we sort firms into a high-beta, mid-beta, and low-beta grouping, based on the sample beta distribution for the firms in the respective subset. Accordingly, we end up with 11 high-beta portfolios, 11 mid-beta portfolios, and 11 low-beta portfolios, with each portfolio containing approximately 33 firms. In Table 8, we...

<table>
<thead>
<tr>
<th>Size portfolio</th>
<th>$\kappa_3$ on $V_{Sz}^U$</th>
<th>$\kappa_4$ on $V_{CF(mkt)}$</th>
<th>Sensitivity ratio</th>
<th>$V_{Sz}^U$</th>
<th>$V_{CF(mkt)}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decile 10 (largest)</td>
<td>0.836 (6.07)</td>
<td>0.080 (1.93)</td>
<td>0.804</td>
<td>0.306</td>
<td></td>
</tr>
<tr>
<td>Decile 9</td>
<td>0.728 (4.38)</td>
<td>0.077 (2.53)</td>
<td>0.652</td>
<td>0.424</td>
<td></td>
</tr>
<tr>
<td>Decile 8</td>
<td>0.748 (4.89)</td>
<td>0.065 (3.34)</td>
<td>0.601</td>
<td>0.446</td>
<td></td>
</tr>
<tr>
<td>Decile 7</td>
<td>0.728 (4.79)</td>
<td>0.057 (3.50)</td>
<td>0.576</td>
<td>0.451</td>
<td></td>
</tr>
<tr>
<td>Decile 6</td>
<td>0.760 (5.21)</td>
<td>0.051 (3.14)</td>
<td>0.612</td>
<td>0.397</td>
<td></td>
</tr>
<tr>
<td>Decile 5</td>
<td>0.751 (5.38)</td>
<td>0.044 (2.93)</td>
<td>0.676</td>
<td>0.391</td>
<td></td>
</tr>
<tr>
<td>Decile 4</td>
<td>0.729 (4.87)</td>
<td>0.047 (3.19)</td>
<td>0.664</td>
<td>0.378</td>
<td></td>
</tr>
<tr>
<td>Decile 3</td>
<td>0.671 (4.24)</td>
<td>0.055 (3.84)</td>
<td>0.631</td>
<td>0.424</td>
<td></td>
</tr>
</tbody>
</table>

The table reports on the conditional variance model given by Eqs. (11) and (12) in Section 4.3, estimated on size-based, decile-portfolio returns. The $\kappa_i$’s are estimated coefficients on the explanatory terms, where $\kappa_3$ is for the $V_{Sz}^U$ term and $\kappa_4$ is for the $V_{CF(mkt)}$ term. The cross-sectional volatility term, $V_{CF(mkt)}$, is formed from our broad firm-level RD about the market return. $V_{Sz}^U$ is the conditional volatility from a univariate GJR GARCH model on the respective size-based portfolio return. T-stats for the respective coefficients are in parentheses, calculated with robust standard errors in accordance with Bollerslev and Wooldridge (1992). The last two columns report the sensitivity ratios that provide information about the relative importance of each explanatory term in the conditional variance equation, see Section 6.2. The sample period is 1988–1996.
present the results for estimating our portfolio-level volatility model, Eqs. (11) and (12), on the returns of these beta-based portfolios. The cross-firm volatility term, $V_{\text{CF}(\text{mkt})}$, is again formed from our broad firm-level RD. We find that the RD term provides reliable incremental information for the future portfolio-level volatility for all 33 cases. Further, the sensitivity measure in the final column of the table for the $V_{\text{CF}(\text{mkt})}$ term seems substantial and is of similar magnitude across the low, mid, and high-beta portfolios.

### 6.4.3. Industry-level results

We also estimate the portfolio-level conditional variance model, given by (11) and (12), in Section 4.3, on fifteen different industry portfolios. Appendix A describes the portfolios and details the results. We find that the RD term provides reliable incremental information for the future industry volatility for 14 of the 15 industries (see Appendix A, Table A2). The sensitivity ratios on the $V_{\text{CF}(\text{mkt})}$ term also seem substantial for these industry portfolios. Appendix A also reports the relation between the volatility of industry-level portfolios and industry-specific firm RD measures (the RD of the firms that comprise the respective industry).

These size-based, beta-based, and industry-based results suggest a generality to our findings. Further, these results suggest that the RD-volatility relation may be better described as a market wide phenomenon, rather than being associated with a specific firm characteristic.

### Table 8
Cross-firm volatility and the future volatility of US beta-based portfolios

<table>
<thead>
<tr>
<th></th>
<th>$\kappa_3$ on $V_{U,k,j}$</th>
<th>$\kappa_4$ on $V_{\text{CF}(\text{mkt})}$</th>
<th>Sensitivity ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$(V_{U,k,j})$</td>
</tr>
<tr>
<td><strong>Panel A: portfolios of low-beta stocks</strong></td>
<td>0.712</td>
<td>0.026</td>
<td>0.53</td>
</tr>
<tr>
<td>Median</td>
<td>0.735</td>
<td>0.027</td>
<td>0.58</td>
</tr>
<tr>
<td>Mean</td>
<td>10</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: portfolios of mid-beta stocks</strong></td>
<td>0.702</td>
<td>0.077</td>
<td>0.61</td>
</tr>
<tr>
<td>Median</td>
<td>0.674</td>
<td>0.076</td>
<td>0.61</td>
</tr>
<tr>
<td>Mean</td>
<td>10</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td><strong>Panel C: portfolios of high-beta stocks</strong></td>
<td>0.605</td>
<td>0.178</td>
<td>0.53</td>
</tr>
<tr>
<td>Median</td>
<td>0.623</td>
<td>0.174</td>
<td>0.55</td>
</tr>
<tr>
<td>Mean</td>
<td>11</td>
<td>11</td>
<td></td>
</tr>
</tbody>
</table>

This table reports on the conditional return volatility for portfolios of high, mid, and low beta stocks. Our sample of firm returns is subdivided to end up with 11 high-beta portfolios, 11 mid-beta portfolios, and 11 low-beta portfolios, with each portfolio containing approximately 33 firms, see Section 6.4.2. For each beta portfolio, we estimate our portfolio-level conditional volatility model, Eqs. (11) and (12) in Section 4.3. The $\kappa$’s are estimated coefficients on the explanatory terms, where $\kappa_3$ is for the $V_{U,k,j}$ term and $\kappa_4$ is for the $V_{\text{CF}(\text{mkt})}$ term. The cross-sectional volatility term, $V_{\text{CF}(\text{mkt})}$, is formed from our broad firm-level RD about the market return. $V_{U,k,j}$ is the conditional volatility from estimating a univariate GJR GARCH model on the respective beta-based portfolio return. The last two columns report on the sensitivity ratios that provide information about the relative importance of each explanatory term in the conditional variance equation, see Section 6.2. The sample period is 1988–1996.
6.5. Robustness: alternate empirical specifications and return densities

We also find that our results are robust to alternate specifications for incorporating RD information into the conditional variance and to alternate return densities that allow for excess kurtosis. For brevity, we report details in Appendix B.

7. Return dispersion, stock turnover, and macroeconomic news

In our introduction, we discuss several plausible explanations for why cross-sectional RD might provide incremental information for future volatility, even after controlling for lagged own-firm return shocks and market-return shocks. Here, to further characterize the nature of cross-firm RD and to possibly assist with the economic interpretation of our primary findings, we examine how RD varies with stock turnover and whether RD is different on macroeconomic-news-release days.

First, following Connolly and Stivers (2003), we form a “market-adjusted relative turnover” (MRTO) that measures the unexpected stock turnover after controlling for the trend in turnover and the normal variation in turnover associated with the absolute market return. MRTO is defined as the residual from the following time-series model.

\[
\ln(\text{TVR}_t) = \psi_0 + \sum_{\tau=1}^{10} \psi_\tau \ln(\text{TVR}_{t-\tau}) + \psi_{11} \text{Abs}(R_{\text{Mkt},t}) + \psi_{12} D_t^\text{Abs} \text{Abs}(R_{\text{Mkt},t}) + \nu_t
\]

(13)

where \(\ln(\text{TVR}_t)\) is the natural log of the average turnover of the firms that comprise our broad market portfolio, \(\text{Abs}(R_{\text{Mkt},t})\) is the absolute value of the our broad-market return, \(D_t^\text{Abs}\) is a dummy variable which equals one when the market return is negative, and the \(\psi\)'s are estimated coefficients.

We also form an analogous “market-adjusted relative return dispersion” (MRRD) using our broad firm-level RD, where MRRD is defined as the residual from a model identical to (13) except that \(\ln(\text{RD})\) replaces \(\ln(\text{turnover})\). Thus, MRRD measures the unexpected RD after controlling for the trend in RD and the normal variation in RD associated with the absolute market return. We find that the correlation between MRTO and MRRD is 0.353, indicating a substantial, positive association between daily turnover shocks and RD shocks.

Second, we are interested in whether the expected RD and expected turnover are related, after first detrending turnover to remove low-frequency variations. Following from Campbell et al. (1993), we detrend the turnover in order to ensure a stationary time series and to measure trading volume relative to the capacity of the market to absorb the volume. Specifically, we take the log of the turnover series and then subtract the 1-year moving average of the log-series where the 1-year moving average is calculated from trading days t-22 to t-272. By lagging the moving average by 1 month, we can capture the current short-term trend in an autoregressive model of the detrended series. Although there is little
evidence of a low-frequency trend in RD over our 1988–1996 period (see Fig. 1), we also similarly detrend RD for this comparison in order to treat the turnover and RD series symmetrically.

We then estimate an expected RD and turnover by fitting an AR(10) model to the respective detrended series. Even with the low-frequency detrending, the autoregressive models capture a substantial degree of predictability with an $R^2$ of 51.9% for the RD series and 45.5% for the turnover series. In the final step, we treat the fitted values from the autoregressive estimation as expected values for each detrended series. We find that these expected RD and expected turnover series have a correlation coefficient of 0.30.

Our turnover results complement the findings in Bessembinder et al. (1996), who document a positive relation between their measure of return dispersion (a Mean Absolute return Deviation across firms or MAD) and turnover. BCS detrend turnover by subtracting a 40-day moving average and find a positive correlation of 0.43 between their MAD and the detrended turnover over their May 1982 through December 1991 sample. Thus, BCS’s method evaluates the relation between the detrended turnover and RD (not detrended) and does not distinguish between the expected or unexpected component of each series. In contrast, our method decomposes each respective series into an expected component (that captures short-term trends only due to the longer-term detrending) and an unexpected component.

Next, we also investigate whether the MRRD is systematically different on days with either a Producer Price Index or unemployment news release (see data discussion in Section 5.4.3). We find that the average MRRD is about 0.45 standard deviations lower on these news-release days. This average MRRD difference is statistically significant at a 0.1% $p$-value.

The evidence in this section suggests a couple of interpretations for the RD-volatility relation. First, our turnover results seem consistent with the interpretation that RD may reflect firm-specific information flows (see Bessembinder et al., 1996; Bekaert and Harvey, 1997). Under this interpretation of RD, our results suggest that these firm-level information flows are persistent. Further, if the firm-level information flows are also correlated across firms, then this explanation could also explain the link between RD and future market-level volatility.

Second, since studies such as Chen et al. (2000), Harris and Raviv (1993), and Shalen (1993) have proposed that high volume is likely to be associated with more diverse beliefs, high RD may also be associated with greater dispersion-in-beliefs and uncertainty about economic prospects. Consistent with this possibility is our finding that RD tends to be relatively low on macroeconomic-news release days. If macroeconomic news releases tend to resolve uncertainty and provide a clearer market signal, this also suggests a positive association between RD and dispersion in beliefs or RD and economic uncertainty. Thus, it seems plausible that our volatility findings may also be related to explanations for intertemporal volatility persistence that rely on imperfect information, diverse beliefs, and/or economic uncertainty (see, e.g., Veronesi, 1999; Brock and LeBaron, 1996; Harris and Raviv, 1993; Shalen, 1993). In our view, the information-flow and uncertainty interpretations are not mutually exclusive, but rather both may contribute to explaining the incremental volatility information in RD.
8. Conclusions

We study the cross-sectional dispersion in daily US stock returns over the 1985–1999 period. Our primary empirical contribution is to demonstrate that return dispersion (RD) contains reliable incremental information about the future traditional volatility of both firm-level and portfolio-level returns. Our empirical work also documents the time-series behavior of daily RD and the relation of RD to other variables such as stock turnover and macroeconomic news.

At the firm level, we find that daily RD provides sizable and reliable incremental volatility information for the majority of individual stocks, where incremental means information beyond that contained in the own-firm lagged return shocks and the lagged market-level return shocks. Further, our results suggest that RD contains more incremental information about a firm’s future volatility than do the lagged market-level return shocks. We find consistent results for a limited sample of Japanese and UK individual stocks.

We also find that the RD contains reliable information about the future traditional volatility of aggregate market-level stock returns. These firm-level and market-level volatility results are consistent over our primary 1988–1996 sample and over our pre-and post-evaluation periods of 1985–1987 and 1997–1999.

We also investigate how the RD-volatility relation varies with a firm’s industry, market capitalization, and market-beta. We find that RD provides reliable incremental information about the future volatility for nearly all of the different industry portfolios, size-based portfolios, and beta-based portfolios. Further, there are no apparent patterns in how the strength of the RD information varies across these different portfolios. We also investigate alternate measures of RD in Appendix A. We find that our broad firm-level RD tends to provide better volatility information than does the dispersion of industry-level returns about the market return or the dispersion of size-based portfolio returns about the market return. Overall, our cross-sectional investigation and our investigation of alternate RD measures suggest that the RD-volatility relation can better be described as a market-wide phenomenon, rather than being associated with a particular firm or industry characteristic.

A natural question is why RD would provide incremental information about the future traditional volatility of stock returns. We are aware of no directly applicable theory on this point and a formal analysis is beyond the scope of this empirical study. Nonetheless, we briefly discuss this question within the context of our findings.

One possibility is that RD captures volatility information about multiple common-factor shocks that cannot be summarized adequately by lagged market-return shocks. This explanation implies that RD should be useful in modeling both market-level and firm-level returns since volatility persistence in common factors should generate volatility persistence at both the firm and market level. The pervasiveness of our findings across both firms and portfolios seems consistent with this possible explanation. However, this possibility suggests that the dispersion in industry-level returns or size-based portfolio returns might contain better information than does our broad firm-level RD, which is at odds with our findings. More broadly, RD may help statistically identify the stock market’s unobservable volatility environment.
RD may also have economic interpretations which suggest a positive association with future traditional volatility. For example, return dispersion may reflect firm-level information flows which are persistent over time. If so, then RD might contain information about future volatility, including index volatility if the firm information flows tend to be cross-sectionally correlated. Another possible economic interpretation is that both RD and traditional volatility may be positively associated with the underlying dispersion-in-beliefs and/or economic uncertainty about the market signal or market state. In Section 7, when exploring the relation between RD, turnover, and macroeconomic-news announcements, we provide some evidence that that seems consistent with this notion.

Our findings suggest several additional avenues for further research. First, our empirical work is an initial effort to incorporate RD information into conditional volatility models for the daily stock returns of individual firms and portfolios. Subsequent work may extend and improve our empirical specifications and estimation methods. Second, recent studies such as Fleming, Kirby, and Ostdiek (2001) and Busse (1999) find evidence that volatility timing appears to be useful in asset allocation decisions. A natural extension of their work is to incorporate the information in RD into volatility timing applications. Third, our findings may have applications in firm-level option pricing and event studies. Finally, future studies that attempt to explain volatility persistence theoretically should take our findings into account.

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Appendix A. Alternate cross-sectional return dispersion (RD) measures

A.1. Decomposition of firm-level RD and alternate RD measures

Consider the following industry-based decomposition of firm-level return dispersion. Starting from Eq. (1), we can subtract and add the industry-portfolio return for each firm i as follows, where firm i’s industry return at time t is denoted as $R_{ind\ i\ t}$

$$RD^2_{CF(mkt)\ t} = \frac{1}{n-1} \sum_{i=1}^{n} \left[ (R_{i\ t} - R_{ind\ i\ t}) + (R_{ind\ i\ t} - R_{Mkt\ t}) \right]^2.$$  (14)
Next, by expanding the squared term and distributing the summation through to each separate additive term, we can rewrite (14) as:

\[
= \frac{1}{n-1} \left[ \sum_{i=1}^{n} (R_{i,t} - R_{\text{ind},i,t})^2 + 2 \sum_{i=1}^{n} (R_{i,t} - R_{\text{ind},i,t})(R_{\text{ind},i,t} - R_{\text{Mkt}}) + \sum_{i=1}^{n} (R_{\text{ind},i,t} - R_{\text{Mkt}})^2 \right].
\] (15)

Note that the middle cross-term above will sum to zero when performing a partial summation only over the firms in a particular industry. Thus, overall, the cross-term will sum to zero across all industries. Then, we can rewrite (15) as:

\[
\text{RD}_2^{\text{CF(mkt)},t} = \frac{1}{n-1} \left[ \sum_{i=1}^{n} (R_{i,t} - R_{\text{ind},i,t})^2 + \sum_{i=1}^{n} (R_{\text{ind},i,t} - R_{\text{Mkt}})^2 \right].
\] (16)

Finally, by denoting the first summation term as \( \text{RD}_{\text{CF(ind)},t}^2 \) (the dispersion of firm returns about the respective industry return) and the second summation term as \( \text{RD}_{\text{CI(mkt)},t}^2 \) (the dispersion of industry returns about the market return), we can rewrite (16) as:

\[
\text{RD}_2^{\text{CF(mkt)},t} = \text{RD}_{\text{CF(ind)},t}^2 + \text{RD}_{\text{CI(mkt)},t}^2.
\] (17)

We use the two terms from this decomposition, \( \text{RD}_{\text{CI(mkt)},t}^2 \) and \( \text{RD}_{\text{CF(ind)},t}^2 \), in additional empirical work to better understand the source of the RD volatility information. The \( \text{RD}_{\text{CF(ind)},t}^2 \) from this decomposition measures firm-level RD about the respective industry, and thus provides a more idiosyncratic firm RD measure.

We also investigate the case where size-based, decile-portfolios are the disaggregate portfolios. We denote the dispersion of the size-decile returns about the market return as \( \text{RD}_{\text{CSz(mkt)},t}^2 \). Our evaluation of size-based dispersion is motivated by the role of size in asset pricing, such as in the widely-used Fama-French three-factor model.

Additionally, to better understand the information in cross-sectional RD and assess the robustness and breadth of the RD-volatility relation, we calculate narrow portfolio-specific measures of firm-level RD. Specifically, we calculate industry-specific firm-level RDs (or the dispersion of firm returns within a specific industry about that industry return) and size-based firm-level RDs (or the dispersion of firm returns about their respective size-based, decile-portfolio return). Each of these measures of cross-sectional RD is calculated using Eq. (1), but substituting for the different \( R_i \)'s and substituting the appropriate portfolio return for \( R_{\text{mkt}} \).

Table A1, Panel A, reports descriptive statistics for the firm-level RDs about the respective industry. We examine 15 different industries, based on the two-digit SIC breakdown from Moskowitz and Grinblatt (1999) (see their Table 1, p. 1254), but we exclude the financial industry, “other” industries, and industries where the average market capitalization is less than one percent of the total stock market capitalization. We form industry portfolio returns using an equally-weighted average return of all firms that have the respective 2-digit SIC code in CRSP. Note that all of the industry-specific RDs
(RD_{CF(ind)}) are substantially positively correlated with our broad firm-level RD (RD_{CF(mkt)}). The average correlation between our broad firm-level RD and the industry-specific firm RDs is 0.39.

Table A1, Panel B, reports descriptive statistics for the dispersion of industry and size-based portfolio returns about the market return (using our 15 industry returns and the eight largest size-based, decile portfolio returns). As one would expect, note that both the mean and the variability of the portfolio-level RD is much smaller than the firm-level RD’s reported in Table 1, Panel B and Table A1, Panel A. However, note that these portfolio-level RDs are substantially correlated with our broad firm-level RD at 0.59 for the dispersion across industry returns and 0.48 for the dispersion across size-based portfolio returns.

A.2. Alternate cross-sectional RDs and future stock volatility

Recall that our broad firm-level RD about the market return ($V_{CF(mkt)}$) provides reliable incremental information about the future traditional volatility for aggregate market-level returns, for nearly all of the different size-based portfolios, market-beta-based portfolios, and industry portfolios, and for the substantial majority of individual stock returns. To explore further the nature of the volatility relations, we next report on the empirical performance of the alternate RD measures in regard to the RD-volatility relation.

To begin with, we estimate variants of (11) and (12) for the conditional volatility of the market-level return where the $V_{CF(mkt)}$ term is replaced by either: (1) the dispersion of industry returns about the market return ($V_{CI(mkt)}$), (2) the dispersion of size-based, decile-portfolio returns about the market return ($V_{CSz(mkt)}$), or (3) the aggregate dispersion of firm returns about their respective industry return ($V_{CF(ind)}$). For the dispersion across industry returns ($V_{CI(mkt)}$), we find that the estimated $\kappa_4$ coefficient on $V_{CI(mkt)}$ is positive for all three periods, but it is statistically significant only in the 1997–1999 period. For the dispersion across size-based portfolio returns ($V_{CSz(mkt)}$), we find that the estimated coefficient on $V_{CSz(mkt)}$ is positive and significant for all three periods, although only at the 10% level for our primary period and the later 1997–1999 period. Next, for the case where the cross-sectional volatility is from the aggregated firm RD about each firm’s respective industry return, $V_{CF(ind)}$, we find that the $V_{CF(ind)}$ results are essentially identical to the results in Table 6, which is not surprising since the aggregated $V_{CF(ind)}$ and our $V_{CF(mkt)}$ are nearly identical with a correlation of 0.99. Overall, we find that our broad firm-level RD about the market ($V_{CF(mkt)}$) generally performs at least as well, and typically better, than these alternate RD measures.

Next, we investigate whether the dispersion of firm returns within industry $j$, $R_{DCF(ind,j)}$, contains reliable incremental information for the volatility of industry $j$’s return. Table A2 presents the results for estimating the conditional variance model given by (11) and (12) on the industry portfolio returns. Under the Case 1 heading in Table A2, we estimate the model with an industry-specific measure of cross-firm volatility, $V_{CF(ind,j)}$, formed from the firm RD about industry $j$’s return for the firms that comprise industry $j$. We find that $V_{CF(ind,j)}$ provides reliable incremental information for the future industry volatility for 7 of the 15 industries (information beyond that contained in the lagged own-industry
Table A1
Descriptive statistics for alternate return dispersions

Panel A: Firm-level RD about the industry return within SIC industries

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.22</td>
<td>1.80</td>
<td>1.70</td>
<td>2.01</td>
<td>1.54</td>
<td>2.08</td>
<td>1.94</td>
<td>2.29</td>
<td>2.32</td>
<td>1.90</td>
<td>2.20</td>
<td>1.98</td>
<td>1.31</td>
<td>1.94</td>
</tr>
<tr>
<td>10th Pct.</td>
<td>1.67</td>
<td>1.27</td>
<td>1.16</td>
<td>1.50</td>
<td>1.03</td>
<td>1.48</td>
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<td>1.73</td>
<td>1.68</td>
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<td>1.58</td>
<td>1.31</td>
<td>1.04</td>
<td>1.24</td>
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<td>25th Pct.</td>
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<td>1.46</td>
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<td>1.68</td>
<td>1.22</td>
<td>1.68</td>
<td>1.56</td>
<td>1.93</td>
<td>1.90</td>
<td>1.53</td>
<td>1.80</td>
<td>1.54</td>
<td>1.12</td>
<td>1.49</td>
</tr>
<tr>
<td>Median</td>
<td>2.13</td>
<td>1.69</td>
<td>1.61</td>
<td>1.92</td>
<td>1.45</td>
<td>1.97</td>
<td>1.84</td>
<td>2.19</td>
<td>2.22</td>
<td>1.78</td>
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<td>75th Pct.</td>
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<td>2.00</td>
<td>1.94</td>
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<td>1.76</td>
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<td>2.23</td>
<td>1.42</td>
<td>2.24</td>
<td>2.50</td>
</tr>
<tr>
<td>90th Pct.</td>
<td>2.88</td>
<td>2.40</td>
<td>2.35</td>
<td>2.59</td>
<td>2.15</td>
<td>2.78</td>
<td>2.60</td>
<td>2.96</td>
<td>3.07</td>
<td>2.56</td>
<td>2.94</td>
<td>2.79</td>
<td>1.61</td>
<td>2.79</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.56</td>
<td>0.58</td>
<td>0.55</td>
<td>0.54</td>
<td>0.50</td>
<td>0.63</td>
<td>0.60</td>
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<td>0.62</td>
<td>0.69</td>
<td>0.30</td>
<td>0.70</td>
</tr>
<tr>
<td>Autocorrelation</td>
<td>0.31</td>
<td>0.17</td>
<td>0.34</td>
<td>0.30</td>
<td>0.22</td>
<td>0.25</td>
<td>0.27</td>
<td>0.36</td>
<td>0.25</td>
<td>0.29</td>
<td>0.28</td>
<td>0.22</td>
<td>0.28</td>
<td>0.23</td>
</tr>
<tr>
<td>Avg. no. of firms</td>
<td>80</td>
<td>39</td>
<td>31</td>
<td>93</td>
<td>24</td>
<td>39</td>
<td>40</td>
<td>94</td>
<td>41</td>
<td>54</td>
<td>28</td>
<td>158</td>
<td>18</td>
<td>131</td>
</tr>
<tr>
<td>Corr. w/RD$_{CT(mkt)}$</td>
<td>0.48</td>
<td>0.26</td>
<td>0.29</td>
<td>0.40</td>
<td>0.27</td>
<td>0.34</td>
<td>0.43</td>
<td>0.57</td>
<td>0.43</td>
<td>0.38</td>
<td>0.41</td>
<td>0.36</td>
<td>0.41</td>
<td>0.33</td>
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</tbody>
</table>

Panel B: Dispersion of disaggregate portfolio returns about the market return

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.37</td>
<td>0.21</td>
<td>0.24</td>
<td>0.28</td>
<td>0.34</td>
<td>0.43</td>
<td>0.53</td>
<td>0.14</td>
<td>0.35</td>
<td>0.11</td>
<td>0.25</td>
<td>0.35</td>
<td>0.11</td>
<td>0.23</td>
</tr>
<tr>
<td>10th Pct.</td>
<td>0.35</td>
<td>0.35</td>
<td>0.59</td>
<td>0.59</td>
<td>15</td>
<td>8</td>
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</tbody>
</table>

This table reports basic descriptive statistics for the alternate daily return dispersions (RD) evaluated in this study. Panel A reports on the firm-level RD about the respective industry’s return within specific SIC industries. The 2-digit SIC groups are: Mining, 10–14; Food, 20; Paper, 26; Chemical, 28; Petroleum, 29; Primary Metals, 33; Fabricated Metals, 34; Machinery, 35; Electrical Equip., 36; Transport Equip., 37; Manufacturing, 38–39; Other Transport., 41–47; Utilities, 49; Dept. Stores, 53; Retail, 50–52 and 54–59. Panel B reports on the dispersion of disaggregate portfolio returns about the market return, both for size-decile portfolio returns about the market return (excluding the two smallest deciles) and the dispersion of industry portfolio returns about the market return. All statistics are for the 1988–1996 period and all return statistics are reported in percentage form.
return shocks). For the other 8 industries, the estimated coefficient on $V_{CF(ind_j)}$ is positive but insignificant. Under the Case 2 heading in Table A2, we estimate the model with the conditional cross-sectional volatility from our broad-market firm RD, $V_{CF(mkt)}$. We find that the $V_{CF(mkt)}$ provides reliable incremental information for the future industry volatility for 14 of the 15 industries. The sensitivity measure in the final column of the table for the $V_{CF(mkt)}$ term also seems substantial. Results for the alternate periods, 1985–1987 and 1997–1999 are qualitatively similar. Overall, these industry results indicate a generality to our findings across industries. Further, the results suggest that the RD-volatility relation may be better described as a market-wide phenomenon since the broad $V_{CF(mkt)}$ is typically a more important explanatory term than the industry-specific $V_{CF(ind_j)}$.

Next, we also estimate our portfolio-level volatility model, Eqs. (11) and (12), on the returns of the eight largest size-based decile-portfolios with one difference from the model in Table 7. We use a portfolio-specific RD to form $V_{CF(sz_j)}$ (formed from the firm RD about size-decile j’s return for the firms that comprise size-decile j). Here, we find that $V_{CF(sz_j)}$ provides reliable incremental information for the future portfolio volatility for the six smaller-firm portfolios (deciles 3–8). For the two largest decile-portfolios, the estimated $\kappa_4$ on the cross-sectional volatility term is also positive, but statistically

<table>
<thead>
<tr>
<th>SIC</th>
<th>Case 1: Ind. RD</th>
<th>Case 2: Market RD</th>
<th>Sensitivity ratio (Case 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\kappa_3$ on $V_{Ind}^{U}$</td>
<td>$\kappa_4$ on $V_{CF(ind_j)}$</td>
<td>$\kappa_3$ on $V_{Ind}^{U}$</td>
</tr>
<tr>
<td>10–14</td>
<td>0.627 (2.69)</td>
<td>0.086 (4.31)</td>
<td>0.602 (2.77)</td>
</tr>
<tr>
<td>20</td>
<td>0.793 (4.99)</td>
<td>0.069 (2.24)</td>
<td>0.959 (6.40)</td>
</tr>
<tr>
<td>26</td>
<td>0.903 (4.56)</td>
<td>0.044 (1.07)</td>
<td>0.637 (2.94)</td>
</tr>
<tr>
<td>28</td>
<td>1.010 (5.09)</td>
<td>0.005 (0.15)</td>
<td>0.614 (3.17)</td>
</tr>
<tr>
<td>29</td>
<td>0.744 (2.41)</td>
<td>0.145 (3.22)</td>
<td>0.755 (3.18)</td>
</tr>
<tr>
<td>33</td>
<td>0.897 (4.72)</td>
<td>0.035 (0.93)</td>
<td>0.531 (2.84)</td>
</tr>
<tr>
<td>34</td>
<td>0.866 (5.75)</td>
<td>0.032 (1.21)</td>
<td>0.064 (4.23)</td>
</tr>
<tr>
<td>35</td>
<td>0.829 (5.24)</td>
<td>0.041 (1.37)</td>
<td>0.624 (4.09)</td>
</tr>
<tr>
<td>36</td>
<td>0.808 (5.07)</td>
<td>0.081 (2.73)</td>
<td>0.732 (5.00)</td>
</tr>
<tr>
<td>37</td>
<td>0.928 (6.11)</td>
<td>0.031 (0.88)</td>
<td>0.651 (3.71)</td>
</tr>
<tr>
<td>38–39</td>
<td>0.841 (6.23)</td>
<td>0.059 (1.85)</td>
<td>0.665 (5.20)</td>
</tr>
<tr>
<td>41–47</td>
<td>0.963 (5.92)</td>
<td>0.020 (0.50)</td>
<td>0.625 (3.81)</td>
</tr>
<tr>
<td>49</td>
<td>0.912 (4.95)</td>
<td>0.046 (2.22)</td>
<td>0.978 (5.94)</td>
</tr>
<tr>
<td>53</td>
<td>0.787 (4.46)</td>
<td>0.140 (2.05)</td>
<td>0.541 (3.53)</td>
</tr>
<tr>
<td>50–52, 54–59</td>
<td>0.979 (6.18)</td>
<td>0.014 (0.46)</td>
<td>0.709 (4.96)</td>
</tr>
</tbody>
</table>

This table examines the incremental information content of RD for the future traditional volatility of industry portfolio returns. The table reports on two variations of the portfolio-level conditional volatility model given by Eqs. (11) and (12) in Section 4.3. For case one, the cross-sectional volatility is from the cross-firm return dispersion about industry j’s return ($V_{CF(ind_j)}$) for the firms in industry j. For case two, the cross-sectional volatility is from our broad firm-level RD about the market ($V_{CF(mkt)}$). $V_{Ind}^{U}$ is the industry’s conditional volatility from a univariate GJR GARCH model, and the $\kappa$’s are estimated coefficients. T-stats for the respective coefficients are in parentheses, calculated with robust standard errors in accordance with Bollerslev and Wooldridge (1992). The last two columns report the sensitivity ratios (as defined in Section 6.2) that provide information about the relative importance of each explanatory term in the conditional variance equation for Case 2. The sample period is 1988–1996.
insignificant. As compared to the results in Table 7, the $V_{CF(sz,j)}$ information is inferior to the broader $V_{CF(mkt)}$ term for all of the portfolios except decile-5 and decile-3.

Overall, our findings suggest the following. Our broad firm-level RD about the market return performs at least as well, and typically better, than the alternate RD measures. RD provides reliable incremental information about the future volatility for nearly all of the different industry and size-based portfolios. There are no obvious patterns in how the strength of the RD information varies across these different portfolios.

Appendix B. Other robustness issues

B.1. Alternate empirical specification for conditional firm volatility that includes RD information

A simple alternate specification that examines the volatility information in RD is the following augmented GARCH(1,1) model:

$$R_{i,t} = \beta_0 + \beta_1 R_{i,t-1} + \beta_2 R_{Mkt,t-1} + \varepsilon_{i,t}$$

$$V_{i,t} = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + (\alpha_2 + \alpha_3 D_{t-1}) \varepsilon_{Mkt,t-1}^2 + \alpha_4 RD_{CF(mkt),t-1}^2 + \alpha_5 V_{i,t-1}$$

where $R_{i,t}$ is the daily return of the individual firm, $R_{Mkt,t}$ is the daily market-level return, $\varepsilon_{i,t}$ is the firm return residual, $V_{i,t}$ is the firm’s conditional variance, $\varepsilon_{Mkt,t}$ is the return residual obtained from estimating the system given by (9) and (10) in Section 4.2, $D_t$ is a dummy variable that equals one if $\varepsilon_{Mkt,t}$ is negative and is 0 otherwise, and $RD_{CF(mkt),t}^2$ is the squared cross-firm return dispersion about the market return. The $\alpha$’s and $\beta$’s are coefficients to be estimated. Thus, this specification jointly examines the information content of the lagged own-firm return shocks, lagged market-level return shocks, and lagged RD.

The simplicity of this specification is attractive. However, the disadvantage of this specification, as compared to our IMCS model in Section 4.2, is that the lagged firm-level return shocks, the lagged market-level return shocks, and the lagged RD are all forced to follow the same decay rate for the t-2 and older shocks through the estimated $\alpha_5$ coefficient.

Our results from estimating this alternate specification also indicate that the lagged RD provides reliable, incremental information about future firm volatility. For example, for the larger firms in our sample, 63% of the estimated $\alpha_4$’s are positive and statistically significant at a 5% $p$-value. Thus, this estimation reinforces our conclusions from our principal models examined in the main text.

Another alternate model is to modify our IMCS model in Section 4.2 by using the simple $RD_{t-1}^2$ as the explanatory variable in the conditional variance equation in place of the conditional cross-sectional volatility (CSV), formed per Section 3.2. We estimate this alternate model for the conditional volatility of the market-level return and the 15 industry returns from Table A2. While the results are qualitatively similar, we find that our conditional CSV outperforms the simple $RD_{t-1}^2$ when modeling the conditional volatility.
of the market-level returns and 14 of the 15 industry returns. In our view, this seems intuitive since our conditional CSV uses information from 10 lags of RD, which acts to smooth the RD series and provide more information.

B.2. Alternate conditional return densities

It is well known that individual firm returns typically do not meet the assumption of conditional normality due to excess kurtosis, even with standardized residuals. Accordingly, we also re-estimate our IMCS model, given by (5) and (6), but using a ‘Student’s \( t \)’ density in the maximum likelihood estimations to allow for greater kurtosis in the conditional returns. We find that the coefficient on the RD term is positive and statistically significant for 66.7% of firms for our estimations using the ‘Student’s \( t \)’ density, which is comparable to the results in Table 4.

References