Does Stock Return Synchronicity Really Matter In Terms of Stock Price Informativeness?

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Abstract

Durnev *et al.* (2003) find that firms with lower synchronicity exhibit higher association between current returns and future earnings, indicating more informative stock prices. We revisit this issue and show that after properly accounting for its strong correlation with size, stock return synchronicity reveals nothing about stock price informativeness or the amount of firm-specific information reflected in stock prices. Then again, we find that large (small) firms have higher (lower) price informativeness. In contrast to Durnev *et al.* (2003) our results indicate that without controlling for size, high synchronicity firms display higher price informativeness. Overall, this paper provides little support for the informational interpretation of synchronicity, and it demonstrates that it is inappropriate to use synchronicity as a measure for stock price informativeness.

JEL classification:

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I. Introduction

There is a growing body of research arguing that stocks with lower stock return synchronicity, measured as the R^2 from the market model, have more firm-specific information incorporated in their prices, i.e., lower synchronicity means more informative stock prices[1]. At the aggregate country level, existing evidence is largely consistent with this view. Morck *et al*. (2000) find that stock prices move together more in emerging markets than in developed markets, and countries with lower stock return synchronicity are associated with stronger investor property rights. Similarly, Jin and Myers (2006) show that stocks in countries where firms are more opaque from an investors' perspective have higher average R^2s. These studies' findings suggest that countries with lower stock return synchronicity should have more informative stock prices, since strong property rights and greater transparency promote informed trading, which facilitates the capitalization of firm-specific information into stock prices.

However, at the firm-level, the evidence on the relationship of synchronicity and price informativeness is mixed and even conflicting. On one hand, according to Durnev, Morck, Yeung and Zarowin (2003), firms with lower synchronicity exhibit stronger association between current returns and future earnings, indicating more informative stock prices. Additionally, Durnev *et al.* (2004) document a negative relation across industries between synchronicity and the efficiency of capital budgeting. They suggest that since more informative stock prices facilitate more efficient corporate investments, this finding can also be explained by the view that synchronicity is inversely related to the informativeness of stock prices. On the other hand, Pontiff (2006) provides a theory arguing that idiosyncratic risk is the single largest cost faced by arbitrageurs. Consequently, stocks with lower synchronicity (higher idiosyncratic risk) should be associated with fewer arbitrageurs, higher level of mispricing, and less informative stock prices. Empirically, Kelly (2005) finds that low synchronicity stocks are smaller, younger, less liquid and with fewer informed trades, which is consistent with the notion that firms with low synchronicity have poor information environment and thus less informative prices. In addition, Ashbaugh-Skaife, *et al*.

[1] Following Durnev *et al.*(2003), we define stock price informativeness as the amount of information that stock prices contain about future earnings.

(2006) show that synchronicity is not a consistent measure of stock price informativeness internationally. In particular, they find that, in the U.S. and Germany, firms with lower synchronicity actually have lower stock price informativeness.

In our opinion, the view of low levels of synchronicity as an indicator of greater informativeness, which has recently been espoused by a number of studies (e.g. Piotroski and Roulstone (2004), Chan and Hameed (2006), and Ferreira and Laux (2007)) and is based on the findings of Durnev *et al*. (2003), is problematic. We base this belief on the fact that besides the aforementioned conflicting findings and arguments about the relation between synchronicity and informativeness at the firm level, there is a salient and robust size effect observed in all studies. Specifically, larger firms have higher stock price synchronicity (See Roll (1988), Kelly (2005), Chan and Hameed (2006), Ferreira and Laux (2007)). If highly synchronous returns truly signal less informative stock prices, as suggested by Morck *et al*. (2000, 2003), we could infer that the market is informationally less efficient for large firms. However, this argument is somewhat counter-intuitive, given the fact that large firms are more actively traded, have more firm-specific information disclosed by the popular press and media, and are followed by more analysts than small firms. It is also inconsistent with findings of prior studies. For example, Collins *et al.* (1987) find that price-based earnings forecasts outperform univariate time-series forecasts by a greater margin for large firms than for small firms, which suggests that the stock prices of larger firms are more informative.

Our aim is to explore the fundamental question of whether there is any relation between synchronicity and informativeness. Specifically, we examine whether lower synchronicity signifies higher price informativeness. We conduct a firm-level study[2] of U.S. firms and utilize the direct measure of price informativeness used by Durnev *et al.* (2003), which is based on ex post accounting information[3]. We find that large firms have more informative stock prices than small firms. More importantly, there is virtually no relationship between synchronicity and price

[2] Technically speaking, our study is at portfolio level, since our price informativeness measures are estimated at portfolio level.
[3] This measure is originally proposed by Collins *et al*. (1994).

informativeness, once the size effect on synchronicity has been fully accounted for[4]. Although Roll (1988) demonstrates that this size effect cannot fully account for the cross-sectional differences in R^2 across firms, our study demonstrates that the association between synchronicity and price informativeness is essentially driven by size effect.

We also show that, without controlling for size, firms with high synchronicity will exhibit high stock price informativeness. This result is in line with the findings for U.S. firms in Ashbaugh-Skaife, *et al*. (2006), and illustrates that their evidence of a positive relationship between synchronicity and informativeness can be attributed to the fact that their empirical tests utilize no control variables. Moreover, our study reveals the sensitivity of the Durnev *et al.* (2003) findings to alternative empirical designs and demonstrates that their results are likely to have been derived from unrepresentative samples and unreliable estimates of the price informativeness measures.

This paper makes several contributions to the existing literature. First, we show that, after accounting for its strong correlation with size, synchronicity reveals nothing about stock price informativeness or the amount of firm-specific information reflected in stock prices. This finding implies that it is inappropriate to use stock return synchronicity as a measure of price informativeness, and therefore, we may need to cautiously reinterpret the results of several studies that have used such a measure (e.g. Piotroski and Roulstone (2004), Chan and Hameed (2006), and Ferreira and Laux (2007)). Second, our results reconcile the conflicting empirical results of Durnev *et al.* (2003) and Ashbaugh-Skaife, *et al*. (2006). Both of these studies show a significant relation between synchronicity and informativeness in the U.S., however as shown here their results are likely due to imperfect empirical design. Third, Roll (1988) concludes that the low R^2 observed from popular asset pricing models can be either due to the capitalization of firm-specific information, which predicts a negative relation between R^2 and price informativeness, or due to noise trading, which predicts a positive relation between the two variables. Our results actually suggest that the two effects are coexisting without either effect systematically dominating the other.

[4] Specifically, we orthogonalize size and synchronicity, by taking the residuals from the cross-sectional regression of synchronicity on size and industry dummies.

The rest of the paper proceeds as follows. Section II describes the sample selection procedure and the construction of the main variables: stock return synchronicity and stock price informativeness. This section also introduces our empirical framework and control variables. Section III discusses univariate analysis results. Section IV reports regression analysis results and robustness checks. It also contains a discussion of the findings of Durnev *et al*. (2003). Section V concludes the paper.

II. Data, Measures and Empirical Framework

A. Data and Sample Selection

We obtain stock prices and returns from the Center for Research in Security Prices (CRSP) and firms' accounting data from Compustat. The initial sample includes all companies listed in the WRDS CRSP/Compustat merged database for each year from 1980 to 2002. We stop in 2002, since the construction of the price informativeness variables in any year t requires the availability of information in the subsequent three year period, i.e. up to year t+3. We delete entries whose CUSIP identifiers in CRSP append a number other than 10 or 11, in order to eliminate entries for preferred stock, class B stock and similar duplicate entities. We omit financial firms and utility firms (SIC codes in the ranges 6000–6999 or 4900–4999), because their accounting figures are incomparable with those of other firms. We also exclude firms if their industry affiliation is not clear (i.e., SIC codes are missing). Finally, we drop firms that do not have a full year of uninterrupted (weekly) returns data to avoid problems associated with firms that experience IPOs, delisting, or trading halts. After imposing these constraints, we obtain a final sample that contains an average of 2365 firms each year. The number of firms varies across years with a minimum of 1634 firms in 1980 and a maximum of 2872 firms in 2001 (See Table I Panel A).

[Insert Table I here]

B. Stock Return Synchronicity Measure (SYNC)

Since there is no consensus on which asset pricing model is best suited for capturing systematic risks, and in order to be comparable with past studies (e.g., Roll (1988) and Durnev *et al*. (2003, 2004)), our synchronicity (SYNC) measure is computed using the industry-adjusted market model:

$$r_{i,j,t} = \alpha_i + \beta^i_{MKT} R_{M,t} + \beta^i_{IND} R_{IND,j,t} + \varepsilon^i_t \qquad (1)$$

Here, the weekly returns of firm i in industry j (based on the first two digits of the primary SIC code) are regressed on concurrent broad market return $R_{M,t}$ and industry return $R_{IND,j,t}$. We use weekly returns to ameliorate the thin trading and bid-ask bounce problems common in small firms. Both the market and board industry returns are value-weighted averages excluding the firm in question, which prevents any spurious correlations between firm returns and factor returns. This adjustment is important, especially for the industries with few firms. We run the above regression during every fiscal year for each firm[5], and define SYNC as equal to the regression R^2. Since previous studies have shown that large firms tend to have high SYNC, we also use an orthogonal measure of synchronicity, R_SYNC, which allows us to differentiate the synchronicity effect from the size effect and avoid potential multicollinearity problems. R_SYNC is measured as the residual from a pooled regression of SYNC on firm size, industry and year dummies.

C. Measures of Stock Price Informativeness (FINC and FERC)

Following Collins *et al*. (1994) and Durnev *et al*. (2003), we express current stock returns as a function of the current period's unexpected earnings and changes in expected future earnings, and define the informativeness as the ability of current stock returns in tracking expected future earnings. In particular, we estimate the following regression:

$$r_t = a + b_0 \Delta E_t + \sum_\tau b_\tau \Delta E_{t+\tau} + \sum_\tau c_\tau r_{t+\tau} + u_t \qquad (2)$$

where ΔE_t is the change in earnings per share (operating income before depreciation over common shares outstanding) during fiscal year t, scaled by the absolute value of earnings per

[5] We estimate SYNC on the fiscal-year basis in order to better align with our stock price informativeness measures which are based on fiscal-year-end earning information.

share for year t-1[6]. r_t is the annual return for the calendar year when fiscal year t ends.[7] Current change in earnings (ΔE_t) is a proxy for current unexpected earnings. Given the fact that future changes in earnings ($\Delta E_{t+\pi}$) are noisy proxies for changes in current expectations of future earnings, we include future returns ($r_{t+\tau}$) to control for unexpected changes in future earnings. Here, we consider the next three years of earning changes and returns, i.e., τ equals to three.

We measure stock price informativeness in two ways. The first measure of informativeness is the future earnings incremental explanatory power (FINC), which is the increase in the adjusted R^2 of regression (2), compared to the following regression:

$$r_t = a + b_0 \Delta E_t + u_t \qquad (3)$$

The second measure of informativeness is computed by taking the sum of the coefficients on future earnings from regression (2), and defined as future earnings response coefficient (FERC), i.e., $FERC \equiv \sum_{\tau} b_{\tau}$. In our opinion, since FERC is merely capturing the magnitude of the future earnings' coefficients, FINC is a more appropriate measure than FERC for capturing stock price informativeness. Specifically, differences in the magnitude of the aforementioned sum of coefficients do not necessarily lead to differences in price informativeness. For example, if Firm A's FERC is higher than that of Firm B, it simply means that Firm A's current return will increase more than Firm B's given a 1% increase in expected future earnings[8]. In fact, what matters most is the significance level of these coefficients because that is a better indicator of the association of current returns with future earnings, i.e. price informativeness. Therefore, we believe that the relative increase in the explanatory power of the future earnings, which is captured by the

[6] Durnev *et al*. (2003) used the stock price at the beginning of the year as a deflator. However, this may create spurious correlation between returns and earnings changes, since both variables are deflated by stock price at the beginning of the year.

[7] We select this measurement period for r_t to let stock prices incorporate the earning information for fiscal-year t, since the annual earnings announcement occurs after the fiscal year-end.

[8] The positive sign of the b_{τ} coefficients that comprise FERC indicates that current return is correctly reflecting future earnings movements. However, the sign of b_{τ} itself does not guarantee that FERC is a good measure of the level of stock price informativeness.

increase of adjusted R-squared, or FINC, is a better measure of informativeness. Nevertheless, for the purpose of comparing our results with those of former studies, we will include both measures in our empirical tests.

D. Empirical Framework

D1. Portfolio-level Analysis

Similar to Durnev *et al*. (2003), we calculate FINC and FERC by performing cross-sectional regressions. In particular, every year, we sort the firms into several portfolios and run the regressions (2) and (3) across firms within each portfolio. This approach essentially provides an average estimate of FERC and FINC for all firms in the same portfolio, and thus it relies on the assumption that firms pooled together are homogenous in terms of stock price informativeness. The first natural dimension for sorting is industry classification, but unlike Durnev *et al*. (2003) who used the two-digit SIC codes classification, we adopt the Fama and French (1997) 12-industries' classification. The sole purpose of using the 12-industries' classification is to make sure that there are at least 30 firms within each portfolio from which we can reliably estimate the regressions.[9] We further divide each industry into three size sub-portfolios[10], whereas Durnev *et al*. (2003) chose to sort on SYNC. Our choice of size, instead of SYNC, is based on our univariate analysis results to be shown in Section III. These results indicate that SYNC can no longer produce significant cross-sectional differences in FERC/FINC after controlling for size meanwhile the differences in FERC/FINC for different size portfolios remain significant after controlling for SYNC (See Table V).

There are several reasons why we did not attempt to measure FINC or FERC on a firm-by-firm basis using time-series regressions. First, we would need at least 20 years of earnings history to estimate such regressions, and doing so would obviously induce a severe survivorship

[9] If we use the two-digit SIC codes and further sort each industry into three sub-portfolios, we will only have, on average, 8 firms left for each portfolio, even though we have about 2366 firms each year. It is impossible to perform a regression with 7 regressors on such a small sample. If we eliminate the industries with inadequate observations, we will be biasing our sample severely towards industries with more firms. As a robustnesss check, we will use the Fama-French 48-industries' classification later.

[10] Size is measured as the logarithm of firm's market capitalization at the end of the previous year (C), adjusted by the concurrent producer price index for finished goods π, i.e., Size = $\ln(C/\pi)$.

bias, i.e., bias our study toward firms with longer histories. Second, there is no guarantee that stock price informativeness will remain the same over such a long period. Finally and more importantly, it would be inappropriate to use a single estimate for the firm's other characteristics (control variables) over a 20-year period. For example, Microsoft should be classified as a small firm 20 years ago, but today it is one of the biggest firms in the world. Simply taking the average across time would yield a meaningless estimate for such a firm's size.

D2. Control Variables

Our multivariate tests control for other factors that can affect stock price informativeness. These are listed below.

(1) Intrinsic predictability of earnings

The association between current returns and future earnings may be weaker for firms with more unpredictable earnings. Moreover, it is well-known that firms with more volatile earnings and more business segments are intrinsically harder to forecast. Here, we measure earnings volatility (EVOL) as the log of the standard deviation of changes in EPS over the past five years[11], i.e., $\ln[stdev(\Delta EPS_t / |EPS_{t-1}|)]$. To measure the firm's degree of diversification (DIVR), we count the number of business segments reported in Compustat for each firm every year.

(2) Growth opportunities

Since growth firms are investing in projects that will generate cash inflows in the future, their stock price should be more forward-looking than that of mature firms. Consequently, this may yield a stronger relation between current return and future earnings for growth firms. To control for this, we include the book-to-market ratio (B/M) and the R&D expenses over total assets ratio (R&D) as control variables in the multivariate tests. B/M measures growth opportunities from the market perspective, while R&D (previously used by Durnev *et al*. (2003)) is a measure solely based on accounting information. One concern for R&D is that it may also

[11] We take the log because the distribution of the earning volatilities is highly skewed with skewness equals to 121.

capture the intrinsic predictability of future earnings. This is because the high uncertainty of the outcomes of R&D investments may make future earnings for firms with high R&D expenses more unpredictable. In this case, higher R&D firms will have lower stock price informativeness.[12]

(3) Information environment

Apparently, stock prices should be more informative for firms with better information environment. Here, we use the number of analysts following (NUM_FCST) the firm from the I/B/E/S summary dataset as a proxy for firm's information environment. Given the concern that the number of analysts following variable may induce multicollinearity because it is highly correlated with firm size (see Hong, Lim and Stein (2000)), we take the residuals from a pooled regression of the log of NUM_FCST on firm size, industry and year dummies, and call them "residual analyst coverage" (R_NUMFCST).

(4) Good or bad news

Basu (1997) showed that bad news is incorporated in earnings in a more timely fashion than good news due to the conservatism principle of the Generally Accepted Accounting Principles (GAAP). Basu also showed that current annual returns (ARET) can be an indicator of whether the firm is releasing good or bad news. Consequently, since good news reflected in current returns tend to be shown in earnings with a delay, good news firms should display a stronger association between current returns and future earnings.

(5) The association between dividends and earnings

Basic finance theory suggests that current stock prices should be ultimately related to expected future dividends, rather than expected future earnings. Even though higher future earnings will generally lead to higher future dividends, this association will be weaker for firms suffering from agency problems. Consequently, for such firms current stock prices may not be very responsive to changes in future earnings expectations, i.e., they may display low FERC and/or FINC, even if this may not necessarily be due to less informative stock prices. We estimate the association between earnings and dividends by taking the R^2 (RDIVD) from the following regression:

[12] Our tests shown in Section IV actually support the latter view.

$$\Delta E_t = a + b_0 \Delta DIV_t + \sum_\tau b_\tau \Delta DIV_{t+\tau} + u_t \qquad \tau = 1, 2, 3 \tag{4}$$

where DIV is dividend per share plus purchase of preferred and common stock per share, and ΔDIV is the change in DIV scaled by the absolute value of previous period's DIV.

(6) Estimation accuracy

As shown in Table I Panel B, there are significant differences in sample size across industries. Industries with many firms should yield more accurate FERC/FINC estimations than those with few firms. Although it is unlikely that the differences in measurement errors will systematically bias our estimation upward or downward, one concern is that differences in measurement errors will lead to heteroskedasticitiy problems in the panel regressions.[13] To address this issue, we use heteroskedasticity-robust (White) standard errors and industry random-effect models.

III. Univariate Analysis

A. Summary Statistics and Simple Correlations

Table II presents summary statistics for the variables described above. Panel A summarizes the variables at firm-level, while the variables in Panel B are either estimated or averaged at industry-size portfolio level. As expected, the portfolio level variables have lower standard deviations and are therefore less subject to problems associated with extreme values. Our stock price informativeness measures (FINC and FERC) are largely positive (73.6% of FINC observations and 58.3% of FERC observations), which shows that, on average, stock prices are predicting future earnings. The statistics also suggest that FERC estimation is more unstable than FINC, as evidenced by its much larger standard deviation and range.

Table III reports simple correlations for the firm-level and portfolio-level variables. Since correlations may change over time, we choose to report the result for a single year, i.e. using 1990 data, but the results for other years are qualitatively the same. From this table, we can see that synchronicity and size are highly correlated with a coefficient of correlation equal to 0.762. By

[13] The measurement errors will not induce the "errors-in-variables" problem, since FERC or FINC are used solely as dependent variables.

introducing the residual synchronicity measure we eliminate most of the correlation between the two variables[14], while the residuals are still highly correlated with the original synchronicity data. Similarly, the number of analysts following and size are highly correlated. Interestingly, our two growth opportunity measures (B/M ratio and R&D expenses) seem to be uncorrelated, with a coefficient of correlation equal to -0.007. This is consistent with our earlier conjecture that R&D expenses may not be measuring growth opportunities, but rather the intrinsic predictability of future earnings.

[Insert Table II & III here]

B. Means of Synchronicity for Size Portfolios

To confirm that there is a size effect on synchronicity, we sort firms into size deciles every year. Table IV Panel A reports the means of synchronicity for each size portfolio across years. Apparently, synchronicity is monotonically increasing with firm size. The average level of synchronicity for the largest firms is 35.9% whereas it is 5.8% for the smallest firms. The difference is large and statistically significant.

C. Means of Price Informativeness for Different Portfolios

The first question we want to answer is whether large firms have high or low stock price informativeness. Every year firms are first sorted by industry, using the Fama-French 12 industries' classification, and then divided into three size groups. As shown in Table IV Panel B Part 1, there is a significant and monotonic positive relation between size and FERC/FINC. This is consistent with our intuition and prior findings of Collins, *et al.*(1987). We obtain the same result when we first sort firms into growth (B/M ratio) deciles, instead of industries (See Part 2).

Similarly, we sort firms every year by either industry or growth opportunities first and then divide firms into three synchronicity groups every year. Since it is highly likely that, given the high correlation between size and synchronicity, we are still sorting on size, it is not surprising that we

[14] This correlation is not equal to zero for the 1990 subsample. However, since the regression used to estimate residuals is performed for the whole sample the correlation will become zero, if estimated for the whole sample.

find high synchronicity firms are associated with high stock price informativeness. The results using the residual synchronicity measure confirm this conjecture. After extracting the size effect, the association between synchronicity and FINC/FERC becomes insignificant and non-monotonic. This result also suggests that the positive relation between synchronicity and price informativeness, discovered by Ashbaugh-Skaife, *et al*. (2006) for U.S. firms, is driven by not controlling for size.

To further confirm that what really matters in terms of price informativeness is size, rather than synchronicity, we independently sort firms into size quintiles and residual synchronicity quintiles[15]. In Table V, cross-sectional differences in FINC/FERC are mostly insignificant across synchronicity portfolios. In contrast, FINC and FERC are increasing with firm size in nine out of ten cases.

[Insert Table IV & V here]

IV. Multivariate Analysis

A. Panel Regressions

Here, firms are first sorted by Fama-French 12-sector industry and then divided into three size groups every year, as discussed in Section II-D1. We proceed by estimating the following equation that describes price informativeness for industry-size portfolio i in year t:

$$\begin{aligned} FINC/FERC_{i,t} &= \alpha + \beta_1 RSYNC_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 B/M_{i,t} + \beta_4 RND_{i,t} + \beta_5 EVOL_{i,t} \\ &+ \beta_5 DIVR_{i,t} + \beta_6 RNUMFCST_{i,t} + \beta_7 ARET_{i,t} + \beta_8 RDIVD_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (5)$$

Year dummies are also included. Variables are defined in Table II. We use both industrial fixed-effects and random-effects panel regressions. The fixed-effects model provides a good control of the endogenous industrial fixed effect. Meanwhile, the random-effects model can estimate the equation more efficiently in the presence of a heteroskedasticity problem, although it requires the strict exogeneity assumption.

[15] One merit of independent sorting is that the results are not sensitive to sorting order. However, an independent sorting procedure may create imbalanced sample sizes across portfolios. This problem is particularly severe when we independently sort on size and synchronicity, because size and synchronicity are highly correlated. For example, it is very hard to find observations for the smallest firms that are also in highest synchronicity quintile. Therefore, to avoid this problem, we use the residual synchronicity measure.

Table VI shows that in the absence of any control variables synchronicity is positively related to stock price informativeness, which is consistent with the findings of Ashbaugh-Skaife, *et al*. (2006). It also shows that residual synchronicity is never significant in explaining FINC or FERC, and that the signs of its coefficients are changing with different models[16]. Large firms have higher stock price informativeness in most cases. One exception is when we use FERC as dependent variable and include earnings volatility as a control variable. This result, in conjunction with the fact that after the inclusion of earning volatility all the other variables lose their explanatory power, actually suggests that the FERC measure is very sensitive to earnings volatility. However, as discussed before, we believe that the explanatory power of future earnings (FINC) is a more convincing measure of price informativeness than the magnitude of the sum of future earnings coefficients (FERC). Moreover, as we will show later on, when we use more parsimonious industry classifications, the size coefficient regains its significance in the FERC regressions.

The signs of the other control variables' coefficients are mostly as expected. Growth stocks, i.e., stocks with low B/M ratios, have more forward-looking stock prices and a greater association between current returns and future earnings. Firms with unpredictable future earnings, i.e., firms with greater earnings volatility, have lower stock price informativeness. The negative coefficient of R&D expenses is consistent with the notion that R&D expenses are primarily capturing the (poor) earnings predictability, rather than growth opportunities. Greater analyst following makes stock prices more informative. Finally, we find that a stronger association between dividends and earnings (i.e. high RDIVD) increases the association between current returns and future earnings, although this effect is only reflected in certain cases.

[16] The changing signs for RSYNC coefficients are more convincing evidence than insignificant t-statistics, because the t-statistics in our study, as well as other studies which have used price informative measures as dependent variables, are subject to the generated regressant problem. Specifically, the measurement errors in dependent variables, which are generated from another regression, will inflate the standard errors of estimated coefficients and bias toward insignificant findings. However, this problem will not bias the coefficient estimations. Therefore, the changing signs of RSYNC coefficients still provide strong evidence showing that the relation between synchronicity and price informativeness is, at most, random. This would be true, even if the coefficients were statistically significant. Also it seems that this problem is not very severe, given the fact that we still obtain significant results for several other explanatory variables. In addition, to our knowledge, there is no econometric method that can adjust (or even estimate) the measurement errors in a regressant, like FINC, which is the R-square from another regression.

[Insert Table VI here]

B. Robustness Checks

B1. Alternative Industry Classification

Using the Fama-French 12 industries' classification may not fully account for differences across industries. Therefore, we also use the more parsimonious Fama-French 48 industries' classification. To maintain a decent sample size in each portfolio required for estimating the regressions used to obtain the FINC and FERC measures, we further divide each industry into two, instead of three, size groups every year. We also eliminate portfolios whose error degrees of freedom in the regressions performed to estimate FERC are less than 10[17]. From Table VII Panel A, we can see that our former results are largely preserved. Residual synchronicity remains insignificant in every regression model.

B2. Portfolios Sorted by B/M Ratios

One possible criticism for our study is that grouping firms on size first may artificially increase the explanatory power of size in future regression analysis. In order to alleviate this concern, we use the B/M ratio as the second sorting variable after sorting firms by industry using the Fama-French 48 industries' classification. The use of the B/M ratio as a sorting variable is motivated by the fact that it does not bias towards increasing the explanatory power of either synchronicity or size. Table VII Panel B shows that this sorting procedure does not alter our main results.

[Insert Table VII here]

C. Explaining the Results of Durnev et al. (2003)

So far, we have shown that the association between synchronicity and price informativeness is spurious and purely driven by the size effect. However, it is still unclear why

[17] In other words, we require each portfolio to have at least 18 firms (notice that the FERC regression has seven regressors), because it is meaningless to estimate a regression with less than 10 error degrees of freedom.

Durnev *et al*. (2003) find a significantly negative relation, given the fact that they also include size as a control variable in their regression analysis.

First, we try to replicate their cross-industry tests that yield their strongest results. After sorting all firms solely by four-digit SIC codes every year, we estimate FINC/FERC for firms within each four-digit SIC industry. Initially, we obtain 7979 industry portfolios in total and an average of 347 industry portfolios each year. However, only 1779 portfolios, representing merely 22% of our initial sample, have enough observations to perform the regressions for the FINC/FERC estimation. To make matters worse, among these portfolios, only 491 portfolios or just 6% of the firms in the initial sample have more than 10 error degrees of freedom for the FINC/FERC estimations. Second, we mimic their industry-matched-pairs methodology by first grouping the firms into two-digit SIC industries and then dividing each industry into two synchronicity groups. The same problems as with the cross-industry tests emerge here as well, wherein more than 43% of the initial portfolios are dropped due to insufficient observations when estimating FINC/FERC. Again, only 32% of the firms in the initial sample have more than 10 error degrees of freedom for the FINC/FERC estimations[18].

Overall, the empirical design of Durnev *et al*. (2003) is severely biased towards industries with more firms. We conclude that their results are likely products of unrepresentative samples and unreliable estimates for FINC/FERC.

VII. Conclusion

This paper shows that after properly accounting for its correlation with size, stock return synchronicity does not reveal anything about stock price informativeness or the amount of firm-specific information reflected in stock prices. On the other hand, we find that size does influence the level of stock price informativeness. Large firms have higher synchronicity and higher price informativeness. Without controlling for size, high synchronicity firms will exhibit higher price

[18] The replications of the Durnev *et al.*(2003) tests we attempted produced similar subsamples as those in their study. For example, their cross-industry test for 1995 is based on 88 portfolio observations, whereas we obtain 82 portfolios for that year. Moreover, for the industry-matched-pairs tests, they report 94 portfolios (47 pairs) for 1995, whereas, following their prescribed procedure, we obtain 117 portfolios for that year.

informativeness, which is in line with the finding of Ashbaugh-Skaife, *et al.* (2006) for U.S. firms. We also infer that the results of Durnev *et al*. (2003) are likely to be derived from unrepresentative samples and unreliable estimates. Overall, this paper provides little support to the informational interpretation of synchronicity, and it demonstrates that it is inappropriate to use synchronicity as a measure for stock price informativeness. Future studies should possibly explore why large firms have high synchronicity, and try to explain the cross-sectional differences in synchronicity from a non-informational perspective.

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Table I
Sample Distribution

Panel A. By year		Panel B. By Fama-French 12 industries	
Year	Number of firms	Industries	Number of firm-years
1980	1634	Consumer Non-durables	4652
1981	1986	Consumer Durables	2186
1982	2024	Manufacturing	9713
1983	1964	Energy	2736
1984	1916	Chemicals	1818
1985	1976	Business Equipment	11404
1986	1939	Telephone and TV	1423
1987	1650	Shops	6902
1988	2274	Health	5480
1989	2300	Other	8093
1990	2354	Finance	0
1991	2380	Utilities	0
1992	2422		
1993	2564		
1994	2709		
1995	2747		
1996	2727		
1997	2800		
1998	2811		
1999	2872		
2000	2778		
2001	2872		
2002	2762		
Total	54401	Total	54401

Table II
Summary Statistics

In Panel A, we report the summary statistics of the main variables across all firms and years. Stock return synchronicity (*SYNC*) is the unadjusted r-squared from the industry-adjusted market model estimated using weekly returns for fiscal year t. R_SYNC are the residuals from a pooled regression of SYNC on firm size, industries and year dummies. Firm size (*SIZE*) is measured as the logarithm of firm's market capitalization C at the end of previous year adjusted by concurrent producer price index for finished goods π, i.e., Size = ln(C/π). Book-to-market (*B/M*) is the book value of total common equity for fiscal year t-1 divided by the firm's market capitalization at the end of previous year. RND is the ratio of R&D expenses over total asset. Earning volatility (EVOL) is the log of standard deviation of percentage changes in EPS for past five years. Diversification (DIVR) is the number of business segments reported in Compustat for each firm every year. NUM_FCST is the number of analysts following the firm from I/B/E/S summary dataset. R_NUMFCST are the residuals from a pooled regression of the log of NUM_FCST on firm size, industries and year dummies. In Panel B, firms are first sorted by Fama-French 12 industries classification first and then divided into three size groups every year. FERC and FINC are stock price informativeness measures as described in section II (C), and RDIVD is the measure for the association between earnings and dividens as described in section II (D2). They are estimated for each industry-size portfolio. All the other variables are the equally-weighted averages of the corresponding firm-level variables for each industry-size portfolio. The sample period for the data is from 1980 to 2002. Financial and utilities industries are omitted (SIC codes in the ranges 6000–6999 and 4900–4999).

Panel A. Firm-level data

Variables	N	Mean	Std.dev.	Min	25%	Median	75%	Max
Synchronicity Measures								
SYNC	54401	0.158	0.153	9.9×10^{-8}	0.042	0.107	0.226	0.887
R_SYNC	54401	0.000	0.114	-0.428	-0.075	-0.013	0.060	0.643
Control Variables								
SIZE	54401	6.860	2.063	-1.249	5.356	6.697	8.218	15.310
B/M ($\times10^{-2}$)	54370	0.143	3.729	-0.907	0.031	0.056	0.095	506.453
RND	31962	0.075	0.134	0.000	0.008	0.035	0.094	3.703
EVOL	31928	-0.661	1.424	-4.903	-1.618	-0.912	0.917	10.142
DIVR	53660	1.815	1.328	1.000	1.000	1.000	2.000	11.000
NUM_FCST	54401	4.668	6.972	0.000	0.000	2.000	6.000	51.000
R_NUMFCST	54401	0.000	0.679	-3.602	-0.385	0.082	0.476	2.419
ARET	54401	0.204	1.004	-0.984	-0.219	0.062	0.394	110.6

Panel B. Portfolio-level data (Sorted by industry and size)

Variables	N	Mean	Std.dev	Min	25%	Median	75%	Max
Informativeness Measures								
FINC	690	0.093	0.168	-0.609	-0.004	0.051	0.155	1.076
FERC	690	0.110	0.368	-1.040	-0.039	0.015	0.147	3.373
Synchronicity Measure								
M_RSYNC	690	0.001	0.043	-0.160	-0.025	-0.003	0.022	0.209
Control Variables								
M_SIZE	690	7.012	1.934	3.674	5.293	6.828	8.652	11.259
M_B/M ($\times10^{-2}$)	690	0.166	0.586	-0.446	0.053	0.076	0.112	11.455
M_RND	688	0.048	0.051	0.000	0.017	0.032	0.053	0.351
M_EVOL	570	-0.695	0.780	-2.495	-1.227	-0.685	-0.040	1.727
M_DIVR	690	1.928	0.634	1.101	1.441	1.737	2.268	4.550
M_RNUMFCST	690	0.005	0.192	-0.781	-0.115	-0.005	0.113	0.971
M_ARET	690	0.201	0.319	-0.508	-0.006	0.178	0.334	2.542
RDIVD	690	0.135	0.208	0.000	0.011	0.045	0.172	0.999

Table III
Simple Correlation Coefficients of the Main Variables

Panel A reports the simple correlation coefficients of the main variables across all firms and years. Panel B provides the correlation coefficients across industry-size portfolios and years. The data used is from 1990.

Panel A. Correlation Matrix at Firm-level
(for 1990 data)

	R_SYNC	*SIZE*	*B/M*	*RND*	*EVOL*	*DIVR*	*NUM_ FCST*	*R_ NUM FCST*	*ARET*
SYNC	0.824	0.762	-0.254	-0.120	-0.361	0.329	0.661	0.128	0.279
R_SYNC		0.273	-0.108	-0.067	-0.123	0.122	0.272	0.117	0.187
SIZE			-0.343	-0.166	-0.502	0.403	0.830	0.092	0.271
B/M				-0.007	0.236	0.022	-0.308	-0.077	-0.130
RND					0.236	-0.196	-0.098	0.054	-0.009
EVOL						-0.161	-0.438	-0.080	-0.171
DIVR							0.260	-0.066	-0.043
NUM_FCST								0.631	0.246
R_NUMFCST									0.067

Panel B. Correlation Matrix at Portfolio-level (Sorted by industry and size)
(for 1990 data)

	FERC	*RDIVD*	*M_SIZE*	*M_B/M*	*M_RND*	*M_ EVOL*	*M_ DIVR*	*M_RNU MFCST*	*M_ ARET*	*M_ RSYNC*
FINC	0.502	-0.138	0.247	-0.532	-0.103	-0.210	0.042	0.151	0.244	0.189
FERC		0.028	0.593	-0.401	-0.363	-0.605	0.472	0.349	0.076	0.504
RDIVD			0.059	0.051	0.156	-0.113	0.178	0.046	0.145	0.195

Table IV
Univariate Analysis

In Panel A, we sort the firms into SIZE deciles every year, and report the mean and standard deviation (in parenthesis) of SYNC for each SIZE decile. In Panel B, we report means and standard deviations (in parentheses) of FINC or FERC across years. In Part (1) of Panel B, firms are first sorted by Fama-French 12 industries classification and then divided into three SIZE, SYNC or R_SYNC groups every year. For Part (2) of Panel B, firms are first sorted into deciles based on B/M and then divided into three SIZE, SYNC or R_SYNC groups every year. Variables are defined in Table II. * and ** indicate significance at the 5%-, and 1%-levels, respectively.

Panel A: Mean of SYNC

Sorted by	Small D1	D2	D3	D4	D5	D6	D7	D8	D9	Large D10	Q10-Q1 [t-stat]
SIZE	0.058 (0.060)	0.072 (0.071)	0.083 (0.079)	0.101 (0.093)	0.121 (0.106)	0.145 (0.121)	0.174 (0.137)	0.207 (0.150)	0.256 (0.166)	0.359 (0.184)	0.302*** [120.00]

Panel B: Mean of informativeness measures

(1) Control for Industries

	Low	Medium	High	High – Low [t-stat]
SIZE Groups				
FINC	0.044 (0.166)	0.099 (0.166)	0.137 (0.160)	**0.092**** **[6.05]**
FERC	0.028 (0.207)	0.111 (0.401)	0.192 (0.437)	**0.164**** **[5.14]**
SYNC Groups				
FINC	0.066 (0.190)	0.088 (0.180)	0.139 (0.160)	**0.074**** **[4.50]**
FERC	0.042 (0.378)	0.047 (0.476)	0.185 (0.581)	**0.143**** **[3.13]**
R_SYNC Groups				
FINC	0.095 (0.165)	0.080 (0.168)	0.122 (0.181)	0.027 [1.68]
FERC	0.129 (0.463)	0.076 (0.287)	0.051 (0.531)	-0.078 [-1.69]

(2) Control for Book-to-Market Ratio

	Low	Medium	High	High – Low [t-stat]
SIZE Groups				
FINC	0.029 (0.075)	0.057 (0.094)	0.113 (0.119)	**0.084**** **[9.10]**
FERC	-0.201×10^{-3} (0.120)	0.027 (0.112)	0.123 (0.295)	**0.123**** **[6.08]**
SYNC Groups				
FINC	0.042 (0.097)	0.063 (0.106)	0.090 (0.093)	**0.048**** **[5.43]**
FERC	0.004 (0.132)	0.042 (0.384)	0.069 (0.214)	**0.065**** **[4.06]**
R_SYNC Groups				
FINC	0.090 (0.159)	0.091 (0.180)	0.124 (0.190)	**0.033*** **[2.03]**
FERC	0.073 (0.495)	0.125 (1.252)	0.079 (0.610)	0.005 [0.10]

Table V
Mean of Informativeness Measures by Size and Residual Synchronicity Measure

Each year we group the firms into 25 portfolios by independently sorting on SIZE and R_SYNC. Reported are the averages of FINC and FERC for each SIZE-R_SYNC portfolio across years. Variables are defined in Table II. Sample standard deviations are reported in parentheses. * and ** indicate significance at the 5%-, and 1%-levels, respectively.

Independent Sorting by SIZE and R_SYNC

Panel A. Mean of FINC

	R_SYNC Q1 (Low)	Q2	Q3	Q4	R_SYNC Q5 (High)	High – Low [t-stat]
SIZE	-0.023	-0.016	0.010	0.010	0.049	0.072
Q1 (Small)	(0.197)	(0.154)	(0.033)	(0.027)	(0.129)	[1.22]
	0.013	0.033	0.033	0.059	0.063	0.050
Q2	(0.193)	(0.058)	(0.055)	(0.103)	(0.109)	[1.09]
	0.044	0.053	0.062	0.055	0.042	-0.002
Q3	(0.058)	(0.063)	(0.089)	(0.077)	(0.083)	[-0.09]
	0.099	0.059	0.084	0.087	0.084	-0.014
Q4	(0.123)	(0.055)	(0.094)	(0.092)	(0.096)	[-0.46]
SIZE	0.098	0.151	0.182	0.167	0.142	0.044
Q5 (Large)	(0.073)	(0.129)	(0.108)	(0.124)	(0.110)	[1.60]
Large – Small	**0.120***	**0.167****	**0.173****	**0.157****	**0.092***	
[t-stat]	**[2.56]**	**[3.95]**	**[7.32]**	**[5.94]**	**[2.62]**	

Panel B. Mean of FERC

	R_SYNC Q1 (Low)	Q2	Q3	Q4	R_SYNC Q5 (High)	High – Low [t-stat]
SIZE	0.600	0.009	-0.024	-0.004	-0.001	**-0.601****
Q1 (Small)	(1.021)	(0.076)	(0.125)	(0.025)	(0.115)	**[-2.81]**
	0.178	-0.010	-0.022	0.007	0.000	-0.178
Q2	(0.520)	(0.031)	(0.065)	(0.079)	(0.247)	[-1.48]
	0.009	-0.005	0.023	0.052	0.028	0.019
Q3	(0.062)	(0.050)	(0.070)	(0.098)	(0.137)	[0.61]
	0.019	0.024	0.167	0.072	0.062	0.043
Q4	(0.083)	(0.186)	(0.364)	(0.195)	(0.191)	[0.98]
SIZE	0.057	0.188	0.207	0.184	0.123	0.066
Q5 (Large)	(0.165)	(0.238)	(0.363)	(0.372)	(0.232)	[1.12]
Large – Small	**-0.543***	**0.179****	**0.230****	**0.187***	**0.124***	
[t-stat]	**[-2.52]**	**[3.44]**	**[2.88]**	**[2.41]**	**[2.29]**	

Table VI
Industrial Fixed-/Random-effect Panel Regressions of Stock Price Informativeness Measures on Synchronicity and Control Variables

This table reports results of regressions of price informativeness (FINC and FERC) on synchronicity (M_SYNC and M_RSYNC) using the Fama-French 12 industries' classification to create industry-size portfolios. Every year firms are first sorted by industry based on the Fama-French 12 industries' classification and then divided into three size groups. FERC, FINC and RDIVD are estimated for each industry-size portfolio. All the other variables are the equally-weighted averages of the corresponding firm-level variables for each industry-size portfolio. Variables are defined in Table II. For fixed-effect panel regressions, the t-statistics reported in brackets are calculated using heteroskedasticity-robust standard errors. * and ** indicate significance at the 5%-, and 1%-levels, respectively.

	Dependent Variable:									
Independent Variables	*FINC*					*FERC*				
	Model I	Model II	Model III	Model IV	Model V	Model I	Model II	Model III	Model IV	Model V
M_SYNC	**0.412****					**0.615****				
	[6.41]					**[4.16]**				
M_RSYNC		0.193	0.201	0.031	0.014		-0.470	-0.485	-0.396	-0.422
		[1.23]	[1.26]	[0.19]	[0.10]		[-1.25]	[-1.28]	[-0.99]	[-1.27]
M_SIZE		**0.021****	**0.020****	**0.039****	**0.035****		**0.042****	**0.041****	0.005	-0.008
		[6.45]	**[5.80]**	**[4.27]**	**[5.65]**		**[5.72]**	**[5.50]**	[0.27]	[-0.56]
M_B/M			**-1.813****	**-1.974****	-0.621			0.659	1.358	1.689
			[-2.79]	**[-3.36]**	[-0.65]			[0.23]	[0.48]	[0.74]
M_RND			0.043	0.030	**-0.373****			-0.224	-0.194	-0.452
			[0.24]	[0.19]	**[-3.06]**			[-0.60]	[-0.54]	[-1.54]
M_EVOL				0.025	0.015				**-0.137****	**-0.162****
				[1.05]	[0.97]				**[-2.70]**	**[-4.37]**
M_DIVR				-0.001	0.021				0.037	0.022
				[-0.03]	[1.24]				[0.57]	[0.54]
M_RNUMFCST				**0.170****	**0.142****				0.046	0.030
				[3.55]	**[3.97]**				[0.50]	[0.34]
M_ARET				0.011	0.017				0.079	0.079
				[0.59]	[0.68]				[1.29]	[1.36]
RDIVD				0.077	**0.166****				0.019	0.091
				[1.91]	**[5.28]**				[0.18]	[1.20]
No. of observations	690	690	688	568	568	690	690	688	568	568
R-square (%)	20.61	21.00	21.36	32.27	24.62	13.15	15.14	15.19	16.21	14.48
Industrial Fixed or Random Effects	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Ramdom Effect	Fixed Effect	Fixed Effect	Fixed Effect	Fixed Effect	Ramdom Effect
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VII
Robustness Analysis: Using an Alternative Industry Classification and Creating Industry-Size and Industry-B/M Protfolios

This table reports results of regressions of price informativeness (FINC and FERC) on residual synchronicity (M_RSYNC) using the Fama-French 48 industries' classification to create industry-size and industry-B/M portfolios. In Panel A, every year firms are first sorted by industry using the Fama-French 48 industries' classification and then divided into two size groups. FERC, FINC and RDIVD are estimated for each industry-size portfolio. In Panel B, every year firms are first sorted by industry using the Fama-French 48 industries' classification and then divided into two B/M groups. FERC, FINC and RDIVD are estimated for each industry-B/M portfolio. We drop portfolios whose error degrees of freedom in the FERC estimation regression are less than 10. All the other variables are the equally-weighted averages of the corresponding firm-level variables for each portfolio. Variables are defined in Table II. For fixed-effect panel regressions, the t-statistics reported in brackets are calculated using heteroskedasticity-robust standard errors. * and ** indicate significance at the 5%-, and 1%-levels, respectively.

	Panel A. Sorting on Fama-French 48 industries and Size				Panel B. Sorting on Fama-French 48 industries and B/M			
	Dependent Variable:				Dependent Variable:			
Independent Variables	*FINC*		*FERC*		*FINC*		*FERC*	
	Model I	Model II	Model I	Model II	Model I	Model II	Model III	Model IV
M_RSYNC	0.017 [0.12]	0.004 [0.03]	-0.222 [-0.52]	-0.219 [-0.66]	-0.002 [-0.01]	0.065 [0.37]	-0.404 [-0.75]	-0.339 [-0.73]
M_SIZE	**0.024**** **[2.97]**	**0.023**** **[3.64]**	**0.052*** **[2.45]**	**0.032*** **[2.13]**	**0.037**** **[3.74]**	**0.032**** **[3.70]**	**0.058*** **[2.05]**	**0.046*** **[2.02]**
M_B/M	**-2.174*** **[-2.50]**	**-2.218*** **[-2.36]**	0.832 [0.63]	0.062 [0.03]	-1.554 [-1.59]	-1.160 [-1.17]	-1.920 [-1.53]	-1.319 [-0.50]
M_RND	-0.314 [-1.73]	**-0.275*** **[-2.28]**	-0.146 [-0.32]	**-0.829**** **[-3.00]**	**-0.646**** **[-3.40]**	**-0.354**** **[-2.93]**	-0.569 [-1.30]	**-0.941**** **[-2.91]**
M_EVOL	-0.020 [-1.01]	-0.021 [-1.58]	-0.050 [-1.05]	**-0.103**** **[-3.18]**	-0.007 [-0.35]	**-0.034**** **[-2.49]**	-0.030 [-0.58]	-0.053 [-1.45]
M_DIVR	-0.022 [-1.46]	0.014 [-1.51]	0.005 [0.14]	-0.036 [-1.72]	-0.008 [-0.45]	0.009 [0.96]	-0.044 [-1.01]	**-0.050*** **[-2.04]**
M_RNUMFCST	-0.019 [-0.46]	-0.020 [-0.60]	-0.058 [-0.57]	0.058 [0.72]	**0.096*** **[1.96]**	0.057 [1.60]	-0.118 [-1.05]	-0.026 [-0.26]
M_ARET	0.021 [1.03]	0.020 [0.91]	0.189 [1.83]	**0.159**** **[2.89]**	0.027 [1.09]	0.033 [1.36]	0.130 [1.45]	0.095 [1.47]
RDIVD	-0.005 [-0.17]	-0.001 [-0.05]	-0.070 [-1.01]	-0.029 [-0.46]	-0.057 [-1.82]	-0.049 [-1.62]	-0.030 [-0.35]	0.004 [0.05]
No. of observations	920	920	920	920	922	922	922	922
R-square (%)	16.12	12.22	17.37	13.57	15.09	11.49	10.91	7.38
Industrial Fixed or Random Effects	Fixed Effect	Random Effect	Fixed Effect	Ramdom Effect	Fixed Effect	Random Effect	Fixed Effect	Ramdom Effect
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes