MiFID II affects sell-side analyst incentives in Europe, forcing analysts to justify the value they add. While the number of analysts decreases, the average stock return synchronicity with the market also decreases, implying an improvement in price informativeness. The decrease in synchronicity is larger for firms that are more important for the analysts and brokers covering them. It is also asymmetric and substantially larger for negative market movements. Our results suggest that, by changing incentives, MiFID II not only improves the quality of individual analyst work, but also achieves an improvement in the aggregate stock price informativeness.

Keywords: MiFID II; price informativeness; sell-side analysts; stock return synchronicity

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Historically, brokers have provided equity research together with order execution, without charging for it separately. There is a long-running debate on the effects and appropriateness of such soft commissions in paying for equity research, as bundling leads to non-transparent pricing and generates conflicts of interest.1 However, most of this literature focuses on the indirect costs to fund investors, not on the incentive effects on the sell-side analysts themselves.2 At the same time, sell-side equity analysts play an important role in producing and distributing information in the financial markets. Analyst incentives are thus highly important for the information environment in the stock market.3

Implemented in January 2018, the Markets in Financial Instruments Directive II (MiFID II) represents a fundamental change in the market for sell-side analysis in the European Union. MiFID II requires asset managers and broker-dealers to unbundle the cost of equity research from trade execution costs and, hence, to justify how external research contributes to making better investments. The transparency introduced

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by MiFID II forces equity analysts to clearly justify their value and hence fundamentally changes the incentives and the nature of competition.4 At the aggregate level, MiFID II has two broad effects that are likely to have different implications for the firm-specific information available at the firm level. First, the number of analysts covering European firms decreases, potentially reducing the amount of information available. Second, analysts are incentivized to increase their effort, improving the quality of information available. These effects have been documented by prior literature. However, these studies primarily focus on the incentive effect on individual analysts. For example, Fang et al. (2020), Guo and Mota (2021), and Lang, Pinto, and Sul (2019) all find that the number of sell-side analysts covering European firms decreases, but average research quality improves, as measured by analyst-level forecast error and stock market price reaction to analyst reports. Fang et al. (2020) and Lang et al. (2019) also provide evidence of analyst report contents broadening.

At the firm level, prior studies do not provide clear predictions for stock return synchronicity and price informativeness. Here, by price informativeness, we refer to the degree of stock prices reflecting firm-specific fundamental news. Guo and Mota (2021) report that consensus forecast error decreases, suggesting an improvement in information production. However, similar to Lang et al. (2019), they also report that aggregate analyst informativeness decreases.5 Lang et al. (2019) also report that market reactions to earnings surprises increase. Taken together, these findings might imply both negative and positive changes in stock price informativeness, but none of them tests it directly. In an additional piece of firm-level evidence, Fang et al. (2020) and Lang et al. (2019) both find evidence suggesting that market liquidity decreases.6

In this paper, we take a different approach by studying the impact of MiFID II on stock price informativeness directly. In effect, we ask whether the net impact of the decrease in quantity and the increase in quality of sell-side research is positive or negative on aggregate stock price informativeness, as measured by stock return synchronicity with the market. This question is an important addition to the existing findings on MiFID II. In particular, for assessing the market-wide impacts of the reform, it seems natural not only to focus on what happens at the individual analyst level, but also to assess what happens to firms and the market at the aggregate level. The importance of such aggregate assessment is further underscored by the somewhat contradictory evidence provided by the prior studies discussed above.

To study the impact of MiFID II, we construct a comprehensive dataset of European stocks, including all countries in the European Economic Area (EEA) and Switzerland. We measure stock price informativeness by stock return synchronicity, calculated as the annual correlation of daily stock returns with the daily returns from the market index (Peng and Xiong 2006; Huang, Huang, and Lin 2019). A higher stock return synchronicity with the market reflects less firm-specific information being incorporated into the stock price.7 We confirm our findings by also repeating our analysis using a number of other proxies for stock price informativeness, including return autocorrelation, firm-specific stock return variation, return autocorrelation conditional on trading volume, and R-squared from the market model.8

To have a clean, unaffected comparison group for the European firms affected by MiFID II, we construct a propensity-score-matched control group using the universe of US-listed firms and compare our European sample against these firms. For every European firm, we pick the closest US firm based on size, book-to-market ratio, past return, and analyst coverage.9 We focus on the period from 2015 to 2019 and compare stock return synchronicity in the years before MiFID II to that after it. We define the years from 2017 onwards as post-MiFID II. Formally, the directive came into force in January 2018, but the details of the directive had been finalized in early 2017, and the changes in the structure of the analyst industry take place mostly already in 2017 when the largest reduction in the number of analysts occurs.10

We find that the introduction of MiFID II is associated with a significant reduction in stock return synchronicity, suggesting that stock prices incorporate more firm-specific information. Relative to the US control group, correlation with market decreases by more than 6% points for European firms, an approximately 18% reduction relative to the sample average before MiFID II. This result is statistically significant and economically large. It is also robust to various model specifications, including controlling for firm fixed effects and sector-year fixed effects. What is also notable is that there is virtually no difference in the market correlation between European and the matched US firms in the pre-MiFID II period in 2015–2016. This result suggests that the stock price informativeness of European firms significantly improves following MiFID II.

If the impact of MiFID II is driven by a change in analyst incentives, we might expect it to have a larger effect on firms that are more important to the
analysts covering them and the brokers employing the analysts. To test this prediction, we construct several proxies for the relative importance of firms to the analysts covering them. Similar to Harford et al. (2019), we use within-analyst market capitalization, trading volume, and institutional ownership rankings to measure the importance of a firm to an analyst. We also look at the quality of the analysts covering the firms, based on the average precision of their earnings estimates relative to other analysts covering the same firms. Across all these measures of firm importance to the analyst or broker, more important firms experience significantly larger reductions in return synchronicity. Another indication of increased competitive pressure for analysts covering a given firm is the reduction in analyst coverage of that firm amid MiFID II. Hence, we perform an analysis conditional on the change in the number of analysts covering the firm. We find that firms experiencing a reduction in analyst coverage are also the ones where stock return synchronicity decreases the most, suggesting that the incentive effects of the regulatory change are largest in these stocks.

As MiFID II incentivizes analysts to increase effort, we might expect the information they provide to become more accurate. We test this and find that the quality of European consensus earnings forecasts significantly improves after the adoption of MiFID II, compared to their US counterparts. As the logical next step, we then study the changes in stock return synchronicity, conditional on the changes in consensus forecast error. If the reduction in return synchronicity is driven by better-quality information produced by analysts, we would expect this change to be correlated with the change in the absolute consensus forecast error. Our empirical results are consistent with this prediction. The decrease in synchronicity is significantly higher for stocks where the consensus absolute forecast error decreases. Finally, if consensus forecasts get more accurate, one might expect that earnings surprises relative to the consensus elicit larger stock price reactions. We confirm this prediction empirically. Stock price reactions to earnings surprises are significantly stronger following MiFID II.

A possibly important implication of MiFID II is the directionality of changes in stock return synchronicity. There are several reasons why the information provided by analysts might be more important for negative than for positive returns. First, management is likely to be incentivized to make sure positive news is accurately reflected in the share price, while the same is not necessarily the case for negative news. Hence, analyst-generated information may be particularly important for negative returns. Second, there are general differences in market correlations depending on market conditions, and a relative decrease in synchronicity might cause a larger absolute effect in negative correlations. Finally, information production itself may be asymmetric and depend on the market direction. Motivated by these insights, we study the effect of MiFID II on stock return synchronicity separately during days of negative and positive market returns. We find stock return synchronicity decreases significantly more during negative days than during positive days. This suggests that stock prices incorporate more negative firm-specific information and become less contagious to negative shocks, reducing the systematic negative risk component in stock returns.

Our study makes several contributions. First, we provide novel insights on the impacts of unbundling equity research (e.g., Bender et al. 2021) and the effects of MiFID II specifically. Earlier literature on unbundling focuses mostly on the effects on fund investors and conflicts of interest for brokers, not on analyst incentives. In contrast, prior studies of MiFID II focus largely on the effect on individual analyst incentives and outputs, with very little (and somewhat mixed) evidence of firm- and market-level effects. We show that the net effect of the previously documented analyst- and firm-level changes are that aggregate stock price informativeness significantly improves. This finding is significant for investors, possibly favoring passive investors and disadvantaging active ones. It also has important implications for firms, as more informative stock prices are likely to improve investment efficiency (e.g., Chen, Goldstein, and Jiang 2007).

Our findings on the asymmetric effect of MiFID II on return synchronicity are novel in both the stock return synchronicity literature as well as the literature on MiFID II specifically. We show that the information environment can have a differential effect on negative and positive return synchronicity. This implies that stock prices become less contagious to negative shocks and reduce the negative systematic risk component in stock returns. The decrease in negative return correlations is likely a positive thing for (long) investors with concentrated portfolios, as it limits their exposure to systematic downside risk.

More broadly, a large literature focuses on the information content of analyst estimates and stock recommendations. We contribute to this literature by showing that the institutional environment can have important consequences on the information that analysts produce. Our study is also related to the literature on the determinants of stock price
informativeness and comovement. These include voluntary information disclosure by firms (Haggard, Martin, and Pereira 2008), the enforcement of insider trading laws (Fernandes and Ferreira 2009), news about fundamentals (Albuquerque and Vega 2009) and investor attention (Huang et al. 2019). We show that regulatory reforms can have significant implications on market-wide stock return synchronicity. Our findings are also highly policy-relevant for assessing the successfulness of the MiFID II framework adopted by the EEA. Our results suggest that this reform not only achieved stronger incentives and hence more individual effort by analysts, but also improved the overall information environment while reducing the number of analysts producing the information. In a sense, MiFID II seems to have generated more from less, which might be viewed as an encouraging sign of its overall impact.

Data and Methodology

Sample Construction. We use the introduction of MiFID II to study the effect of analyst incentives on stock return synchronicity. MiFID II became formally effective in January 2018. However, its impact on the sell-side analyst industry appears to begin at least one year before the official implementation. Figure 1 shows the annual reduction in the number of analysts in the entire I/B/E/S universe (as identified by their last EPS forecast in the dataset). There are more than 3,000 analysts covering European firms in 2015. About 13% of the analysts leave the industry in 2017, followed by another 9% in 2018. The figure suggests that the expectation of the implementation of MiFID II in 2017 has already strongly affected sell-side analysts. Therefore, we define Post as a dummy variable that equals one from 2017 onwards, and zero otherwise. Our sample period is from 2015 to 2019, i.e., we include two years before and after 2017 in our analysis.

We construct a comprehensive sample of European firms and match them with US control firms. We obtain daily stock market data and accounting information from Compustat Global for publicly listed firms headquartered in all 31 countries within the European Economic Area (EEA). We also include firms located in Switzerland in the analysis, even though it is not a part of EEA and hence not directly affected by the legislation. Given its capital market is closely integrated with those of the EEA and a large part of the analyst coverage of Swiss firms takes place within the EEA, it seems likely that Switzerland is equally affected by the changes.20 We calculate all stock returns for European firms in Euros. For US firms, we obtain stock market data from the Center for Research in Security Prices (CRSP) and accounting data from Compustat. We obtain earnings per share (EPS) forecast data from IBES and use that to identify analysts covering each firm in our sample. We require that each firm should have sufficient data to compute all variables both before and after 2017. We further require that each firm should have at least one analyst covering it prior to MiFID II. To make sure that our results are not driven by small stocks, we delete firms within the bottom size decile. We winsorize all continuous control variables at the 1% level.

To identify the effect of the MiFID II, we match each European firm with a US control firm, using propensity score matching. Specifically, the propensity score for each stock is estimated via a logit model in the pooled sample of European and US firms within each 2-digit NAICS industry. In the logit model, the dependent variable is a dummy that equals one for a European firm and zero otherwise. Independent variables include market capitalization, book-to-market ratio, and past return from the previous year.21 We first select the US firms with closest propensity scores and then minimize the difference in analyst coverage to obtain the closest match for each European firm in our sample. Our final sample contains 2,817 European firms. Descriptive statistics on the distribution of firms by country and year are reported in the Internet Appendix Table A1.

Figure 1. Reduction in the Total Number of Analysts

This figure shows the net reduction in total number of analysts as a percentage in both the European market and US market each year. Analysts leave the market if they stop providing earnings estimates in I/B/E/S. The numbers are computed based on the number of unique equity analysts in the I/B/E/S universe in each year.
We use STOXX 600 as the European market index and S&P 500 as the US market index. For each calendar year, we compute stock return synchronicity for each European (US) firm as the pairwise correlation in currency-adjusted daily returns between the firm and STOXX 600 (S&P 500). In later sections of this paper, we also consider alternative proxies to capture price informativeness from different perspectives.

### Table 1. Summary Statistics

**A. European firms and matched control firms**

|                    | Mean   | Std.   | p10    | p50    | p90    |
|--------------------|--------|--------|--------|--------|--------|
| Synchronicity      |        |        |        |        |        |
| Correlation        | 0.303  | 0.191  | 0.064  | 0.289  | 0.567  |
| Corr.(Positive)    | 0.195  | 0.162  | -0.005 | 0.185  | 0.414  |
| Corr.(Negative)    | 0.259  | 0.176  | 0.046  | 0.246  | 0.501  |
| Corr.(Difference)  | 0.064  | 0.136  | -0.107 | 0.064  | 0.236  |
| R-sq.(index)       | 0.128  | 0.134  | 0.005  | 0.084  | 0.321  |
| Firm characteristics|        |        |        |        |        |
| Analyst coverage   | 7.675  | 8.684  | 1.000  | 4.000  | 22.000 |
| Market value (EURb)| 3.637  | 9.782  | 0.045  | 0.482  | 8.335  |
| B/M                | 0.773  | 0.907  | 0.151  | 0.528  | 1.484  |
| RoE                | 0.007  | 0.388  | -0.276 | 0.083  | 0.240  |
| Turnover rate      | 1.184  | 1.455  | 0.111  | 0.682  | 2.755  |
| Past return        | 0.068  | 0.403  | -0.391 | 0.035  | 0.527  |
| Volatility         | 0.024  | 0.012  | 0.012  | 0.020  | 0.039  |
| N                  | 25,080 |        |        |        |        |

**B. European firms vs. matched control firms**

|                    | Europe | Control (US) | Control – Europe | Δ Mean |
|--------------------|--------|--------------|------------------|--------|
| Synchronicity      |        |              |                  |        |
| Correlation        | 0.285  | 0.320        | 0.035***         |        |
| Corr.(Positive)    | 0.175  | 0.216        | 0.041***         |        |
| Corr.(Negative)    | 0.255  | 0.263        | 0.008            |        |
| Corr.(Difference)  | 0.081  | 0.047        | -0.033***        |        |
| R-sq.(index)       | 0.120  | 0.136        | 0.015***         |        |
| Firm characteristics|        |              |                  |        |
| Analyst coverage   | 7.621  | 7.328        | 0.107            |        |
| Market value (EURb)| 3.327  | 3.947        | 0.619***         |        |
| B/M                | 0.790  | 0.755        | -0.035**         |        |
| RoE                | 0.042  | 0.027        | -0.069***        |        |
| Turnover rate      | 0.521  | 1.848        | 1.327***         |        |
| Past return        | 0.058  | 0.079        | 0.021***         |        |
| Volatility         | 0.021  | 0.026        | 0.004***         |        |
| N                  | 12,540 | 12,540       | 25,080           |        |

Panel A shows the summary statistics for the firm-year observations in the sample. Correlation is the yearly correlation coefficient between daily stock returns and daily market returns. Corr.(Positive) is calculated as the correlation coefficient between daily stock returns and the market index returns from the trading days when the market index return is positive. Corr.(Negative) is calculated as the correlation coefficient between daily stock returns and the market index returns from the trading days when the market index return is negative. Corr.(Difference) is calculated as Corr.(Negative) minus Corr.(Positive). Analyst coverage is the average number of analysts covering the firm. RoE is return on equity, computed as net income divided by the book value of equity. Turnover rate is calculated as the yearly trading volume divided by the number of shares outstanding. Past return is the stock return from the past year. Volatility is the standard deviation of daily stock returns over each year. Panel B shows a comparison of European firms and US control firms. ** and *** indicate significance at the 5% and 1% levels, respectively.
Similar to Bris et al. (2007), we further explore the asymmetry in stock return synchronicity during positive and negative market returns. We divide all trading days in a calendar year into two groups: positive and negative market return days. We calculate the pairwise correlation of daily returns between a firm and the market index during negative days (Corr. (Negative)) and positive days (Corr. (Positive)). We construct Corr. (Difference), calculated as Corr. (Negative) less Corr. (Positive), to capture the asymmetry in stock return synchronicity. This methodology is similar to Huang et al. (2020) and consistent with the analysis of Ang et al. (2006).

**Description of the Data.** Panel A of Table 1 shows summary statistics for all firms in our sample. On average, the annual market correlation in our sample is about 30%. Panel B compares European firms with their US control firms. The average market correlation between European firms and their US counterparts is similar: the average market correlation for European firms is 29% over the sample period, while the average market correlation for matched US firms is 32%.

**Main Results**

**MiFID II and Stock Return Synchronicity.** In Figure 2A, we plot the average market correlations of European firms and the US controls for the years 2015–2019. Before 2017, European firms and US control firms have nearly identical levels of market correlation. However, after 2017, the average market correlation for European firms decreases visibly compared to their US counterparts. In Figure 2B, we summarize a yearly regression coefficient for an interaction term between Europe and respective year dummies, with the dependent variable being market correlation, and controlling for a number of firm characteristics, as well as firm fixed effects and industry-year joint fixed effects.22 These results are consistent with the conclusion from the simple average chart. Even when controlling for stock characteristics and an extensive set of fixed effects, there is a significant reduction in stock return synchronicity for European firms starting from 2017, the year ahead of MiFID II becoming effective.

To formally test for the decrease in synchronicity following MiFID II, we perform a regression analysis specified as:

\[
\text{Correlation}_{it} = \alpha + \beta \times \text{Europe}_i \times \text{Post}_t + \gamma \times \text{Europe}_i + \theta \times \text{Post}_t + \varphi \times \text{X}_{it} + \epsilon_{it},
\]

where Correlation is the annual correlation of daily stock returns with the daily returns from the market index, Europe indicates firms headquartered in Europe, and Post is a dummy taking the value one if
the year is 2017 or later. \( X \) is a vector of controls, including market value, book-to-market ratio, return on equity, volatility, past stock return, analyst coverage, and turnover rate. In all regression analyses, control variables are standardized to have a mean of zero and a standard deviation of one. Depending on the specification, we also include firm fixed effects and industry-year joint fixed effects based on two-digit NAICS codes.

The results are shown in Table 2. It shows that, while return synchronicity decreases for all stocks, including US stocks, this decrease is significantly larger for European stocks, as shown by the significantly negative coefficient for the \( \text{Europe} \times \text{Post} \) interaction term. The estimates suggest that, compared to matched US firms, European firms on average experience a 6% points decline in the market correlation after MiFID II. This result is statistically significant and economically large relative to the average correlation for all European firms of about 36% before MiFID II. The introduction of MiFID II is associated with a decrease in market correlation of approximately 18%.

**MiFID II and Analyst Incentives.** If the impact of MiFID II on return synchronicity is driven by a change in analyst incentives, we might expect it to have a larger effect for firms that are more important to the analysts covering them and the brokers employing the analysts. To test this prediction, we construct several proxies for the relative importance of firms to the analysts covering them. Similar to the analyst portfolio importance measures of Harford et al. (2019), we use the within-analyst market capitalization, trading volume, and institutional ownership rankings to measure the importance of a firm to an analyst. For each analyst, we rank the firms the analyst covers based on market capitalization, volume, or institutional ownership and scale this ranking by the total number of firms covered by the analyst.

For market capitalization, we also calculate a modified, proportional version of this measure. First, we calculate the market capitalization of each firm, divided by the number of analysts covering it. Then, we use the per-analyst market capitalization to perform the same ranking. The idea behind this measure is that, while larger firms are likely to be more important for the analysts covering them, they are even more important if there are fewer other analysts covering them. In other words, there is scarcity value in coverage. We also calculate the relative average absolute forecast error for all analysts based on all of the firms they cover and use that as an additional proxy for the importance of the firm for the analysts covering it.

We perform the following regression analyses:

\[
\text{Correlation}_{i,t} = \alpha + \beta_1 \times \text{Europe} \times \text{Post}_t \times \text{High imp}_i \\
+ \beta_2 \times \text{Post}_t \times \text{High imp}_i \\
+ \beta_3 \times \text{Europe} \times \text{Post}_t + \varphi \times X_{i,t} + \epsilon_{i,t},
\]

where \( \text{High imp}_i \) is a dummy variable that captures high within-analyst market capitalization (\( \text{High mcap} \)), high proportional market capitalization (\( \text{High prop.mcap} \)), high trading volume (\( \text{High trading volume} \)), high institutional ownership (\( \text{High inst.ownership} \)), or high forecast accuracy (\( \text{High accuracy} \)). Note that, since we control both firm-fixed effects and industry-year fixed effects, \( \text{Europe} \), \( \text{Post} \), and \( \text{Europe} \times \text{High imp} \) are dropped from these regressions.

The results, shown in Table 3, are consistent with our prediction that more important firms experience a larger reduction in stock return synchronicity. Across all these measures of firm importance to the analyst or broker, more important firms experience significantly larger reductions in return synchronicity. This finding is consistent with the prediction that analysts allocate effort strategically based on personal career concerns, as shown by Harford et al. (2019), and hence the stronger incentives have the largest effect on the firms where analysts are incentivized to spend the most effort.

Another auxiliary prediction arising from our main argument is that our results should mainly come from firms with more analyst drops. This is because, in firms with more analyst drops, remaining analysts should have much stronger incentives to produce high-quality firm-specific information, resulting in a bigger reduction in synchronicity with market returns.

To test this prediction and to show the cross-sectional variation of our main results conditional on changes in analyst coverage, we re-examine our baseline regressions by including triple interaction terms with respect to changes in analyst coverage. More specifically, we define \( I(\text{Drop}) \) as a dummy variable that equals one if a firm experiences analyst drops after the adoption of MiFID II, and zero otherwise. We further divide \( I(\text{Drop}) \) into two variables based on the median drop value, and \( I(\text{Drop} = \text{High}) \) \( (I(\text{Drop} = \text{Low}) \) is a dummy variable that equals one if a firm experiences above-median (below-median) analyst drops after the adoption of MiFID II, and
The dependent variable is Correlation, the yearly correlation coefficient between daily stock returns and daily market returns. Post is a dummy that equals one from 2017 onwards, and zero otherwise. Europe is a dummy indicating firms based in Europe. Industry-Year fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

Table 4 confirms our conjecture. In column (1), the coefficient for Europe × Post × I(No Change) is significantly negative. This indicates that, for firms with analyst drops after the adoption of MiFID II, their return synchronicity drops 2.7% more than the rest of the firms. This effect is not only statistically significant, but also economically meaningful, considering the effect for the rest of the firms (the coefficient for Europe × Post) is −5.3%. After we further decompose I(Drop) into I(Drop = High) and I(Drop = Low), column (2) shows that our main results mainly come from firms with more analyst drops. For firms with more analyst drops after the adoption of MiFID II, their return synchronicity drops only 0.7% more than the rest of the firms, which is not statistically significant. Moreover, column (3) shows that the coefficient for Europe × Post × I(No Change) is positive and significant. This indicates that our main result becomes weaker for the subsample of firms without changes in analyst coverage. In column (4), similar results are obtained if we include all the triple interaction terms in the same regression.

Results presented in Tables 3–4 are consistent with our argument that MiFID II provides analysts with more incentive to increase their efforts in producing firm-specific information. Analysts covering firms that are more important and with analyst drops should be more incentivized, resulting in a bigger decline in return synchronicity.

**MiFID II and Forecast Accuracy.** As MiFID II incentivizes analysts to increase effort, it might be expected to induce equity analysts to provide more accurate information. We test this by examining analysts’ earnings forecasts. If MiFID II indeed significantly changes analysts’ incentives to produce better...
estimates, we should expect to see their consensus estimates becoming more accurate. This could serve as an important implication to investors in response to the adoption of MiFID II.

To test this prediction, for each earnings announcement, we calculate absolute consensus forecast error, defined as the absolute difference between analysts’ annual EPS forecast consensus and the actual EPS announced, divided by share price, as a proxy for forecast accuracy. We conduct regressions similar to our main empirical specification and examine whether the absolute forecast error from European firms significantly decreases after the adoption of MiFID II.

The results, shown in Table 5, are consistent with the prediction. The quality of European analysts’ earnings forecasts significantly improves after the adoption of MiFID II, compared to their U.S. counterparts. Column (4) suggests a reduction in absolute forecast error equivalent to 6.6% of its standard deviation.

Given the results on improved forecast accuracy, one would naturally wonder if our main results on return synchronicity mainly come from firms with more improved forecast accuracy. This is because, in firms with more improved forecast accuracy, prices should reflect more firm-specific information due to the high-quality analyst forecasts, resulting in a bigger reduction in synchronicity with market returns.

To test this prediction and to show the cross-sectional variation of our main results conditional on forecast improvement, we re-examine our baseline regressions by including triple interaction terms with respect to changes in forecast accuracy. We define I(Drop) as a dummy variable that equals one if the

| Table 3. MiFID II Impact and Analyst Incentives |
|-----------------------------------------------|
| (1) (2) (3) (4) (5) |
| Europe × Post × High mcap | $-0.018^{**}$ | $-0.012^{**}$ | $-0.021^{***}$ | $-0.002^{**}$ | $-0.014^{***}$ |
| Post × High mcap | $-0.008$ | $-0.007$ | $-0.003$ | $-0.010$ | $-0.008$ |
| Europe × Post × High prop. mcap | $-0.021^{***}$ | $0.002$ | $-0.025^{***}$ | $-0.010$ | $-0.027^{**}$ |
| Post × High prop. mcap | $-0.006$ | $-0.008$ | $-0.006$ | $-0.010$ | $-0.005$ |
| Europe × Post × High trading volume | $-0.051^{***}$ | $-0.050^{***}$ | $-0.048^{***}$ | $-0.048^{***}$ | $-0.054^{***}$ |
| Post × High trading volume | $-0.009$ | $-0.008$ | $-0.009$ | $-0.009$ | $-0.007$ |
| Europe × Post × High inst. ownership | $-0.014^{***}$ | $-0.002$ |
| Post × High inst. ownership | $-0.005$ |
| Europe × Post × High accuracy | $-0.014^{**}$ |
| Post × High accuracy | $-0.02$ |
| Europe × Post | $-0.005$ | $-0.005$ | $-0.004$ | $-0.004$ | $-0.005$ |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Industry-Year FE | Yes | Yes | Yes | Yes | Yes |
| N | 22,295 | 22,295 | 22,309 | 20,398 | 23,475 |
| $R^2$ | 0.833 | 0.833 | 0.833 | 0.832 | 0.833 |

The dependent variable is Correlation, the yearly correlation coefficient. Post is a dummy that equals one from 2017 onwards. Europe indicates firms based in Europe. High mcap indicates firms above median of average relative ranking of market cap. High prop. mcap is a similar ranking using proportional market cap, High inst. ownership and High trading volume use trading volume and institutional ownership, respectively. High accuracy indicates firms covered by more accurate analysts. Industry-Year fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.
Table 4. Stock Return Synchronicity and Change in Analyst Coverage

|                          | (1)       | (2)       | (3)       | (4)       |
|--------------------------|-----------|-----------|-----------|-----------|
| Europe × Post × I(Drop)  | -0.027*** | -0.039**  | -0.035*** |           |
|                          | (0.008)   | (0.010)   | (0.011)   |           |
| Europe × Post × I(Drop = High) | -0.007 | -0.007    |           | -0.003    |
|                          | (0.007)   |           |           | (0.007)   |
| Europe × Post × I(Drop = Low) | -0.007  | -0.007    |           | -0.003    |
|                          | (0.007)   |           |           | (0.007)   |
| Europe × Post × I(No Change) | -0.007  | -0.007    | 0.023***  | 0.010**   |
|                          |           |           | (0.004)   | (0.004)   |
| Europe × Post            | -0.053*** | -0.053*** | -0.069*** | -0.057*** |
|                          | (0.009)   | (0.009)   | (0.007)   | (0.010)   |
| Ln(Market value)         | 0.079***  | 0.078***  | 0.080***  | 0.079***  |
|                          | (0.008)   | (0.009)   | (0.008)   | (0.009)   |
| B/M                      | 0.003     | 0.003     | 0.003     | 0.003     |
|                          | (0.003)   | (0.003)   | (0.003)   | (0.003)   |
| RoE                      | 0.000     | 0.000     | 0.000     | 0.000     |
|                          | (0.002)   | (0.002)   | (0.002)   | (0.002)   |
| Volatility               | 0.002     | 0.002     | 0.002     | 0.002     |
|                          | (0.003)   | (0.003)   | (0.003)   | (0.003)   |
| Past return              | 0.004***  | 0.004***  | 0.004***  | 0.004***  |
|                          | (0.001)   | (0.001)   | (0.001)   | (0.001)   |
| Turnover rate            | 0.007***  | 0.007***  | 0.007***  | 0.007***  |
|                          | (0.002)   | (0.002)   | (0.002)   | (0.002)   |
| Ln(1 + Analyst coverage) | 0.009     | 0.009     | 0.013***  | 0.010***  |
|                          | (0.004)   | (0.004)   | (0.004)   | (0.004)   |
| Firm FE                  | Yes       | Yes       | Yes       |           |
| Industry-Year FE         | Yes       | Yes       | Yes       |           |
| N                        | 25,053    | 25,053    | 25,053    | 25,053    |
| R²                       | 0.833     | 0.833     | 0.832     | 0.833     |

The dependent variable is Correlation, the yearly correlation coefficient between daily stock returns and daily market returns. Post is a dummy that equals one from 2017 onwards, and zero otherwise. Europe is a dummy indicating firms based in Europe. I(Drop) is a dummy variable that equals one if a firm drops analyst coverage after MiFID II. We further divided the subsample with analyst drops into two groups based on its median drop value. I(Drop = High) is a dummy variable that equals one for firms with above-median analyst drops, while I(Drop = Low) is a dummy variable that equals one for firms with below-median analyst drops. I(No Change) is a dummy variable that equals one for firms with no change in analyst coverage before and after MiFID II. Industry-Year fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

Table 6 confirms our conjecture. For example, in column (2), the coefficient for Europe × Post × I(Drop) is significantly negative. This indicates that, for firms with improved forecast accuracy after the adoption of MiFID II, their return synchronicity drops 1.2% more than the rest of the firms. This effect is not only statistically significant, but also economically meaningful, considering the effect for the rest of the firms (the coefficient for Europe × Post) is –6.0%. After we further decompose I(Drop) into I(Drop = High) and I(Drop = Low), column (4) shows that our main result mainly comes from firms with more forecast improvements. For firms with more forecast improvements, their return synchronicity drops 1.3% more than the rest of the firms.

The improvement in forecast accuracy should also have an impact on price reactions to unexpected earnings news. Given the improvements in analysts’ forecast accuracy, European stock prices should react more strongly in response to unexpected earnings news. This price sensitivity can be captured by...
regressing the cumulative abnormal return from the earnings announcement to standardized unexpected earnings. Here, we use the cumulative abnormal return from the \([-1, 1]\) window to capture the price reactions to earnings news, where \(t = 0\) is the earnings announcement day (or the ensuing trading day if the news is announcement in a non-trading day or after markets close). Abnormal returns are computed as the Fama-French three-factor adjusted returns using betas computed from the previous year. Standardized unexpected earnings (SUE) is computed as the difference between the actual EPS announcement and analysts’ EPS forecast consensus, divided by share price. We consider a triple interaction term, SUE \(\times\) Europe \(\times\) Post, to capture the incremental price sensitivity for European firms after the adoption of MiFID II. Results from Table 7 shows that, after the adoption of MiFID II, European firms’ stock prices become more sensitive to unexpected earnings surprises, compared to their U.S. counterparts.

### Table 5. Forecast Accuracy and MiFID II

|               | (1)    | (2)    | (3)    | (4)    |
|---------------|--------|--------|--------|--------|
| Europe \(\times\) Post | -0.076 | -0.097*** | -0.101*** | -0.066 |
|                | (0.043) | (0.032) | (0.031) | (0.036) |
| Europe         | 0.308** | 0.365*** | 0.373*** | -      |
|                | (0.046) | (0.041) | (0.043) | -      |
| Post           | 0.009  | 0.011  | -      | -      |
|                | (0.041) | (0.030) | -      | -      |
| Ln(Market value) | -      | -0.137*** | -0.134** | -0.754*** |
|                | -      | (0.056) | (0.057) | (0.093) |
| B/M            | -      | 0.210*** | 0.188*** | 0.018  |
|                | -      | (0.019) | (0.021) | (0.038) |
| RoE            | -      | -0.125*** | -0.126*** | -0.009 |
|                | -      | (0.018) | (0.017) | (0.017) |
| Volatility     | -      | 0.171*** | 0.172*** | 0.040  |
|                | -      | (0.040) | (0.036) | (0.020) |
| Past return    | -      | -0.178*** | -0.191*** | -0.064*** |
|                | -      | (0.016) | (0.016) | (0.012) |
| Turnover rate  | -      | 0.001  | 0.006  | 0.014  |
|                | -      | (0.033) | (0.028) | (0.045) |
| Ln(1 + Analyst coverage) | -      | -0.103** | -0.109** | -0.049 |
|                | -      | (0.045) | (0.043) | (0.048) |
| Firm FE        | No     | No     | No     | Yes    |
| Industry-Year FE | No   | No     | Yes    | Yes    |
| \(N\)          | 20,761 | 19,665 | 19,665 | 19,390 |
| \(R^2\)        | 0.018  | 0.270  | 0.288  | 0.640  |

The dependent variable is the average absolute forecast error from all analysts covering a firm. For each firm, the absolute forecast error is calculated as the absolute difference between analysts’ EPS forecast consensus and the actual EPS, divided by share price. We winsorize this variable at 5% to avoid outliers, and then scale it by the sample standard deviation. Industry-Year fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

### Additional Results

**Positive versus Negative Return Synchronicity.** The findings of Bris et al. (2007) suggest that a change in the aggregate information environment might be expected to have asymmetric effects on stock return synchronicity, depending on the direction of the market. Their results suggest that short selling may reduce the negative-minus-positive return synchronicity difference, implying that more firm-specific negative information is incorporated. This might be true also of analyst-provided information. Firm management is likely to be incentivized to make sure positive news are accurately reflected in the share price, while the same is not necessarily the case for negative news. Hence, analyst-generated information may be particularly important for negative returns. This would imply that the difference between negative and positive return synchronicity decreases if analysts produce better-quality information.
Another reason that this might happen is that there are general differences in market correlations depending on market conditions, as observed by Ang et al. (2006) and Huang et al. (2020), and a relative decrease in synchronicity might cause a larger absolute effect in negative return correlations. Finally, information production itself may be asymmetric and depend on the market direction. This idea parallels the findings of Veldkamp (2005), who argues that more information is generated at times of economic expansion than in periods of contraction, and that this leads to gradual booms and sudden crashes in asset prices. Brockman et al. (2010) provide empirical support for these predictions, showing that stock comovement is countercyclical, and that the relationship between business cycle and comovement is stronger in countries with less developed financial markets and less transparent information. This might also imply that analyst-generated information is more important in negative returns.

To test these predictions, we perform an analysis similar to Bris et al. (2007), studying the effect of MiFID II on stock return synchronicity separately during days of negative and positive market returns. For each group, we calculate market correlation based on daily observations and run the same regression as Equation (1), except that we replace the dependent variable with Corr.(Positive), Corr.(Negative), and Corr.(Difference), i.e., the difference of market correlation between negative days and positive days.

The results are shown in Table 6. While stock price informativeness improves significantly (decrease in

### Table 6. Stock Return Synchronicity and Change in Forecast Accuracy

| Europe × Post × I(Drop) | (1) | (2) | (3) | (4) |
|-------------------------|-----|-----|-----|-----|
| Europe × Post × I(Drop = High) | – | – | –0.012*** | –0.013*** |
|                           | (0.004) | (0.004) | (0.003) | (0.003) |
| Europe × Post × I(Drop = Low) | – | – | 0.014 | 0.011 |
|                           | – | – | (0.019) | (0.017) |
| Europe × Post             | –0.062*** | –0.060*** | –0.062*** | –0.060*** |
|                           | (0.008) | (0.007) | (0.008) | (0.007) |
| Ln(Market value)          | – | 0.080*** | – | 0.080*** |
|                           | – | (0.009) | – | (0.008) |
| B/M                      | – | 0.003 | – | 0.003 |
|                           | – | (0.003) | – | (0.003) |
| RoE                      | – | 0.000 | – | 0.000 |
|                           | – | (0.002) | – | (0.002) |
| Volatility               | – | 0.002 | – | 0.002 |
|                           | – | (0.003) | – | (0.003) |
| Past return              | – | 0.004*** | – | 0.004*** |
|                           | – | (0.001) | – | (0.001) |
| Turnover rate            | – | 0.007*** | – | 0.007*** |
|                           | – | (0.002) | – | (0.002) |
| Ln(1 + Analyst coverage) | – | 0.013*** | – | 0.013*** |
|                           | – | (0.003) | – | (0.003) |
| Firm FE                  | Yes | Yes | Yes | Yes |
| Industry-Year FE         | Yes | Yes | Yes | Yes |
| N                        | 25,053 | 25,053 | 25,053 | 25,053 |
| R²                       | 0.824 | 0.832 | 0.824 | 0.832 |

The dependent variable is Correlation, the yearly correlation coefficient between daily stock returns and daily market returns. Post is a dummy that equals one from 2017 onwards, and zero otherwise. Europe is a dummy indicating firms based in Europe. For each firm, the absolute forecast error is calculated as the absolute difference between analysts’ EPS forecast consensus and the actual EPS, divided by share price. I(Drop) is a dummy variable that equals one if a firm’s absolute analyst forecast error decreases after MiFID II. We further divided this subsample into two groups based on its median decrease. I(Drop = High) is a dummy variable that equals one for firms with above-median forecast improvement, while I(Drop = Low) is a dummy variable that equals one for firms with below-median forecast improvement. Industry-Year fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.
market correlation) for both positive and negative market return days, the effect is more than twice as large during negative days. Columns 5–6 show that this difference is also statistically significant. For example, after controlling for firm and industry-year fixed effects, the market correlation for European firms falls by 5.4% points more during negative days than during positive days after the introduction of MiFID II. This suggests that stock prices incorporate relatively more firm-specific information during days of negative returns. It also implies stock prices being less contagious to negative shocks and reducing the systematic negative risk component in stock returns.

Alternative Measures of Price Informativeness. In our main analysis, we use the correlation with market index as our main measure of stock return synchronicity and as a proxy for stock price informativeness. In this section, we construct alternative measures of stock price informativeness suggested in the literature and repeat our analysis using these alternative measures.23

The first measure we consider is return autocorrelation (e.g., Hendershott and Jones 2005; Indriawan, Pascual, and Shkilko 2020). We compute daily return autocorrelation in each year. This metric relies on the notion that, in a frictionless market, prices should be

Table 7. Price Sensitivity to Unexpected Earnings News and MiFID II

|                | (1)       | (2)       | (3)       | (4)       |
|----------------|-----------|-----------|-----------|-----------|
| SUE × Europe × Post | 0.393***  | 0.459***  | 0.418***  | 0.274     |
|                | (0.134)   | (0.151)   | (0.141)   | (0.192)   |
| SUE × Europe   | −0.591*** | −0.696*** | −0.687*** | −0.672*** |
|                | (0.202)   | (0.214)   | (0.209)   | (0.239)   |
| SUE × Post     | −0.417*** | −0.475**  | −0.454*** | −0.332    |
|                | (0.151)   | (0.168)   | (0.157)   | (0.199)   |
| Europe × Post  | 0.000     | 0.001     | 0.000     | 0.001     |
|                | (0.003)   | (0.003)   | (0.003)   | (0.004)   |
| Europe         | 0.003     | −0.001    | −0.001    | −         |
|                | (0.003)   | (0.003)   | (0.003)   | −         |
| Post           | −0.004    | −0.004    | −         | −         |
|                | (0.003)   | (0.004)   | −         | −         |
| SUE            | 1.065***  | 1.165***  | 1.170***  | 1.145***  |
|                | (0.247)   | (0.254)   | (0.250)   | (0.283)   |
| Ln(Market value)| −        | −0.005*** | −0.004*** | −0.033*** |
|                | (0.002)   | (0.002)   | (0.008)   |           |
| B/M            | −         | 0.000     | 0.000     | 0.001     |
|                | (0.001)   | (0.001)   | (0.001)   |           |
| RoE            | −         | 0.003**   | 0.002***  | −0.003    |
|                | (0.001)   | (0.001)   | (0.002)   |           |
| Volatility     | −         | −0.001    | −0.001    | 0.001     |
|                | (0.001)   | (0.001)   | (0.002)   |           |
| Past return    | −         | −0.001    | −0.001    | −0.002**  |
|                | (0.001)   | (0.001)   | (0.001)   |           |
| Turnover rate  | −         | −0.002    | −0.002**  | −0.005    |
|                | (0.001)   | (0.001)   | (0.003)   |           |
| Ln(1 + Analyst coverage) | − | 0.004*** | 0.004** | 0.006 |
|                | (0.001)   | (0.001)   | (0.004)   |           |
| Firm FE        | No        | No        | No        | Yes       |
| Industry-Year FE | No        | No        | Yes       | Yes       |
| N              | 20,761    | 19,665    | 19,665    | 19,390    |
| R²             | 0.030     | 0.035     | 0.053     | 0.321     |

The dependent variable is CAR[−1, 1], the cumulative abnormal return from the [−1, 1] window, where t = 0 is the earnings announcement day (or the ensuing trading day if the news is announcement in a non-trading day or after markets close). Standard unexpected earnings (SUE) is defined as the difference between the actual EPS and the EPS forecast consensus, divided by share price. Industry-Year fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.
unpredictable, and stock returns should have zero autocorrelation. Therefore, a reduction in autocorrelation can suggest improvement in market efficiency. Column 1 in Table 9 shows that the coefficients for Europe × Post is significantly negative, suggesting that market efficiency is improved for European firms following the introduction of MiFID II.

The second measure we consider is firm-specific stock return variation (e.g., Fernandes and Ferreira 2009). This measure relies on the notion that stock return innovations linked to market returns are the source of systematic risk, while the remaining return innovations reflect firm-specific idiosyncratic risk. Thus, an increase in firm-specific stock return variation indicates stock prices being more informative on firm-specific news.

We construct firm-specific stock return variation with respect to the market model. In the market model, for each firm-year, the projection of a stock’s excess return on the market is

\[ r_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} \]

where \( \sigma_{im} = \text{COV}(r_{i,t}, R_{m,t}) \) and \( \sigma_m^2 = \text{VAR}(R_{m,t}) \).

Firm-specific return variation is estimated for each firm-year as

\[ \sigma_{ic}^2 = \sigma_i^2 - \frac{\sigma_{im}^2}{\sigma_m^2} \]

From the absolute firm-specific return variation, \( \sigma_{ic}^2 \), we compute the relative firm-specific return variation:

\[ \Psi_i = \log \left( \frac{\sigma_{ic}^2}{\sigma_i^2} \right) \]

Column 2 in Table 9 shows that firm-specific return variation significantly increases for European firms after the adoption of MiFID II.
The third measure we consider is return autocorrelation conditional on trading volume (e.g., Llorente et al. 2002). To construct this for each firm-year, we estimate the following time-series regression using daily returns:

\[ r_{it} = \alpha_i + \beta_i r_{it-1} + \gamma V_{it-1} + \epsilon_{it} \]  

Here, \( V_{it-1} \) is log daily turnover detrended by subtracting a 6-month moving average. The amount of information-based trading is given by the regression coefficient \( \gamma_i \) on the interaction term. Higher values of \( \gamma_i \) indicate more information-based trading, as in periods of high volume, stocks with a high degree of information-based trading tend to display positive return autocorrelation.

Column 3 of Table 9 shows that return autocorrelation conditional on trading volume significantly increases for European firms after the adoption of MiFID II, suggesting more information-based trading.

Finally, the last measure we consider is the R-squared from the market model (e.g., Roll 1988; Morck, Yeung, and Yu 2000; Barberis, Shleifer, and Wurgler 2005). In each calendar year, we regress the currency-adjusted daily returns of each European (US) firm on STOXX 600 (S&P 500), and compute the R-squared from each regression. A high market correlation (R-squared) indicates that the stock price incorporates less firm-specific information (e.g., Durnev et al. 2003). Column 4 of Table 9 shows that R-squared significant decreases for European firms after the adoption of MiFID II.

Overall, results from Table 9 suggest that our main results are robust across different proxies for price informativeness. These additional results also broaden the scope of our analyses on synchronicity.
from other perspectives of price informativeness and market efficiency in general.

**Robustness Checks and Additional Analyses.** In the Internet appendix, we perform a number of robustness checks and additional analyses. These are briefly summarized in this section.

**Robustness Checks.**

1. **Firms with no MTF trading.** MiFID II entails components that are not related to analysts. In particular, the limitations of dark pool trading volumes might affect some of our findings. To test this, we repeat our main analysis for a subsample of European firms that do not have any MTF trading in our sample period. Given MTFs include dark pools, this subsample should not be substantially affected by new rules concerning dark pools. As shown in Appendix Table A2, our findings remain similar when including only firms with no MTF trading.

2. **Excluding Switzerland.** In our main sample, we include firms located in Switzerland in the analysis, even though it is not a part of EEA and hence not directly affected by the legislation. Given its capital market is closely integrated with those of the EEA and a large part of the analyst coverage of Swiss firms takes place within the EEA, it seems likely that Switzerland is equally affected by the changes. In Appendix Table A3, we repeat the analysis excluding Switzerland and obtain similar results, confirming that our findings are not substantially affected by the inclusion of Switzerland.

3. **Alternative sample constructions.** To make sure our findings are not driven by the methodology we use to construct the matched control sample, we perform three robustness check analyses. In Appendix Table A4, instead of using only matched US control firms, we include all US firms into the sample without any matching or limitations, i.e. a control group without any matching. We also construct a second matched control group, using more granular propensity score matching process within each 2-digit NAICS industry and include firm size, book-to-market ratio, past return, return on equity, turnover rate, and volatility (i.e., all firm-level control variables we include in the regressions) as the independent variables. This analysis is reported in Appendix Table A5. Finally, we also extend our sample to include observations from 2014 and re-examine our baseline results in Appendix Table A6. With all of these alternative samples, the results remain similar to our main results from Table 2.

4. **Alternative treatment timing.** In our analysis, we define the years from 2017 onwards as post-MiFID II. Formally, the directive came into force in January 2018, but the details of the directive had been finalized in early 2017, and the changes in the structure of the analyst industry take place mostly already in 2017 when the largest reduction in the number of analysts occurs. In Appendix Table A7, we show that our main results remain qualitatively similar when defining the post-MiFID II period as the beginning of 2018 instead.

5. **Alternative frequencies of observations.** In our main analysis, we compute return synchronicity at an annual frequency. To make sure our findings are robust across different estimation windows, in Appendix Table A8, we construct return synchronicity based on monthly and quarterly frequencies. We repeat the analysis using these two alternative synchronicity proxies and obtain similar results.

**Additional Results.**

1. **Placebo test.** To confirm that our results are driven by the change in analyst incentives, instead of other components of MiFID II, we conduct a placebo test using European firms that have never been covered by any analyst during our sample period. If the general decrease in synchronicity is driven by analysts producing better-quality information, we should not observe a reduction in synchronicity for these firms. Appendix Table A9 shows that there exists no significant change in return synchronicity for this set of European firms after the adoption of MiFID II, confirming our main analysis from an alternative perspective.

2. **Stock price crash risk.** We document that the introduction of MiFID II is associated with a significant decrease in stock return synchronicity, and the effect is significantly larger for negative returns. This can be interpreted as a reduction in exposure to systematic negative risk. Hence, we also explore an idiosyncratic component of negative risk, stock price crash risk. In Appendix Table A10, we find that MiFID II is associated with a significant reduction in stock price crash risk.
3. **MiFID II and variance ratio.** To examine whether MiFID II improves market efficiency, we follow Boehmer and Kelley (2009) and Chen, Kelly, and Wu (2020) to construct variance ratio. Because both positive and negative deviations of variance ratio form one represent stock price movement departing from a random walk, we use \(1 - VR(n,m)\) as a measure of market efficiency, where \(VR(n,m)\) is the ratio of the return variance over \(m\) days to the return variance over \(n\) days, both divided by the number of the days. If prices follow a random walk, the deviation should be zero. Larger magnitude of this deviation reveals weaker market efficiency. Appendix Table A11 shows that MiFID II is associated with improved market efficiency, though the results are not always statistically robust.

4. **MiFID II and price delay.** To test whether MiFID II also affects the speed of stock prices incorporating market-wide information, we construct three different measures of price delay suggested by Hou and Moskowitz (2005) and used by, e.g., Bris et al. (2007) and Busch and Obernberger (2017). These measures all consider market return as a proxy for new information and quantify how average prices adjust to it. Therefore, it is worth noting that these measures do not capture the price reaction to firm-specific information. In Table A12, we find that MiFID II is associated with an increase in price delay. This suggests that the adoption of MiFID II makes stock prices more informative to firm-specific information due to higher quality information production from equity analysts but reduces the speed of price reaction to market-wide information.

5. **MiFID II and future earnings return coefficient.** The future earnings return coefficient (e.g., Durnev et al. 2003) can also capture price informativeness. This is a sum of coefficients obtained from cross-sectional regressions in each year for different groups of firms. In other words, it is no long a firm-level proxy. Even though this proxy is not ideal for our research agenda, we still construct future earnings return coefficient at each 2-digit NAICS industry level and examine whether price informativeness improves for European industries after the adoption of MiFID II. Internet Appendix Table A13 indicates potential increase in future earnings return coefficient for European industries after the adoption of MiFID II, though the results are not statistically significant.

6. **Stock return synchronicity by year.** To confirm that our analysis is not simply capturing ongoing trends unrelated to MiFID II, we perform an analysis of stock return synchronicity, as well as the down-up difference in synchronicity, by year. We include all the interactions between Europe and the year dummies in our main regression and report the results in Internet Appendix Table A14. There is no significant difference between 2016 and 2015 in any of the regression specifications. In 2017, the market correlation decreases by approximately 4.5% points for European firms, relative to the matched US peer firms, and in 2018 this decrease relative to 2015 grows further to 7.0% points, and slightly further to 7.8% points in 2019. This suggests that in 2017, the year leading up to the formal MiFID II implementation, slightly more than half of the full MiFID II effect takes place, and the remainder happens in 2018 and 2019. A similar pattern can be seen for the down-up difference in correlation. The timing of the effect is notable as it helps us confirm that at least part of the effects we measure are directly attributable to changes in analyst incentives, as none of the other MiFID II rules related to trade reporting and dark pools could have plausibly affected the market in 2017.

7. **Alternative correlation and R-squared specifications.** In our analyses, we measure stock return synchronicity using the annual correlation between daily stock returns and daily returns of the aggregate market index. Given there are alternative measures of synchronicity used in prior literature, in this section, we consider six different alternative measures to make sure that our results are not driven by the choice of synchronicity measure. The alternative measures of synchronicity include stock return correlation with a value-weighted market return index of its headquarter country, \(R^2\) from regressions of daily stock return on aggregate market index, value-weighted market index return of its headquarter country, and value-weighted industry index return. Results reported in Internet Appendix Table A15 are very similar to our main results reported in Table 2.

8. **Controlling for institutional ownership.** One potential driver of stock return synchronicity could be the amount of passive investments (e.g., Anton and Polk 2014). Therefore, in Internet
Appendix Table A16, we control for total institutional ownership in our baseline regressions. Even though high institutional ownership indeed generates strong return synchronicity, our baseline result on the reduction of return synchronicity for European firms after the adoption of MiFID II remains qualitatively similar.

Discussion and Conclusion

Our results suggest that the unbundling of equity research fees from trading commissions imposed by MiFID II results in not only individual analysts increasing effort, but also the aggregate stock price informativeness improving, as measured by a decrease in stock return synchronicity. We also confirm the improvement in stock price informativeness using a number of other proxies suggested in the literature. Generally, more informative stock prices may imply that it is more difficult for active investors to outperform, as more of the firm-specific information is already incorporated in stock prices. At the same time, they should benefit from systematic risk factor strategies by reducing the noise in stock prices.

The decrease in synchronicity is largest for stocks that are most important for the careers of the analysts covering them and stocks where the incremental competitive pressure introduced by MiFID II is likely to be the strongest. Taken together, these findings suggest that analyst incentives have an important effect on the amount of firm-specific information incorporated in stock prices. Consistently, we find that the consensus earnings estimates become more accurate following MiFID II. This finding is important for investors that use analyst consensus numbers as inputs for their analysis. Importantly, the reduction in stock return synchronicity is correlated with the reduction in consensus absolute forecast error—i.e., the stocks where information quality improves are also associated with larger reductions in synchronicity.

An important implication to investors is that, as the noise in consensus estimates decreases, the market reactions to earnings surprises become stronger. This means that “beating the consensus” becomes more valuable from the investor’s perspective. While we do not attempt to directly test this, it might also affect the profitability of systematic earnings revision strategies—conceivably reducing the return predictability and making such strategies less profitable.

Testing this prediction remains a topic for further research.

Another important implication is the asymmetric reduction in stock return synchronicity. The fact that stock return synchronicity decreases more for negative returns suggests that analyst-generated firm-specific information is more important for negative stock returns. While this is somewhat intuitive, partly because the management is more incentivized to make sure positive information is incorporated, it also implies that stock prices become less contagious to negative shocks and reduce the negative systematic risk component in stock returns. This assertion is also supported by our results in the Internet Appendix showing that stock price crash risk decreases following MiFID II.

Finally, from a regulatory standpoint, our results suggest that MiFID II, in a sense, achieves a better information environment with fewer analysts producing the information. In other words, we show that the net effect of the decrease in the number of analysts and increase in average effort is an increase in stock price informativeness, as measured by reduced stock return synchronicity. Our study has some important limitations. We focus on a relatively short period around the introduction of MiFID II to minimize the chance of capturing changes driven by other events. In particular, we end our sample period in 2019, partly to avoid the COVID-19 period that might confound any results. It is, of course, possible that some of the effects change over time, so the longer-term implications remain a subject for future research. One possibly fruitful direction for future research is what MiFID II does to the returns of systematic trading strategies, in particular ones that make use of analyst-provided information.

Another important consideration is that some of our US control firms might be, to some extent, also affected by MiFID II, as some brokers may choose to have global policies for equity research and hence also change the treatment of research related to US firms. However, if anything, this would make it less likely for us to find results, as the difference between the treatment (European) and control (US) groups would be smaller than in the case where no US firms are affected. This would imply that our results are possibly smaller in magnitude that the full effect of research unbundling.

Taken together, our findings suggest that while MiFID II results in a reduction in the number of sell-
side analysts covering European stocks, it is also associated with an increase in stock price informativeness. These results highlight the importance of analyst incentives in information production, as well as the importance of the institutional environment in determining such incentives.

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Notes
1. See, e.g., Bogle (2009).
2. See Bender et al. (2021) for a comprehensive review of the literature.
3. See, e.g., Harford et al. (2019) on the effect of career concerns on analyst outputs.
4. MiFID II includes other elements as well, discussed in more detail in Section "Main Results."
5. In both of these studies, aggregate analyst informativeness is measured as the sum of all absolute market-adjusted returns of forecast revision dates divided by the sum of absolute market-adjusted abnormal returns of all trading days, similar to e.g. Frankel, Kothari, and Weber (2006) and Lehavy, Li, and Merkley (2011).
6. Neither of these studies attempts to establish whether the reduction in liquidity is related to sell-side analyst regulations or other components of MiFID II.
7. See, e.g., Durnev et al. (2003).
8. These analyses are discussed in detail in Section 4.2. We explore other aspects of price informativeness and market efficiency in Internet Appendix Sections A3.3–A3.5, and A3.7.
9. To avoid the results being driven by small, illiquid stocks, we exclude the smallest 10% of firms from our sample. In the Internet Appendix, we show an analysis without propensity score matching and without limiting firm size, confirming that this limitation and the matching methodology do not materially change our findings.
10. In the Internet Appendix Section A2.6, we show that our results are not sensitive to this definition of treatment timing.
11. This prediction is supported by the findings of Harford et al. (2019), who show that analysts focus their effort strategically on the most important firms they cover, driven by personal career concerns.
12. This is consistent with the results of Bris, Goetzmann, and Zhu (2007), who find that in countries in which short selling is feasible and practiced, the negative-minus-positive synchronicity difference is lower, suggesting that more firm-specific negative information is incorporated.
13. For example, Ang, Chen, and Xing (2006) and Huang et al. (2020) observe that market correlations depend on market conditions.
14. This idea parallels the findings of Veldkamp (2005), who argues that more information is generated at times of economic expansion than in periods of contraction, and that this leads to gradual booms and sudden crashes in asset prices. Brockman, Liebenberg, and Schutte (2010) provide empirical support for these predictions.
15. In Internet Appendix Section A3.2, we show that stock price crash risk also decreases amid MiFID II.
16. Fang et al. (2020), Guo and Mota (2021), and Lang et al. (2019) all find that the number of sell-side analysts covering European firms decreases, but average research quality improves. Fang et al. (2020) and Lang et al. (2019) also find suggestive evidence that market liquidity decreases. Liu and Yezege (2020) find that MiFID II is successful in separating research and execution services and levelling the playing field, with smaller broker-specific trading volume responses to revisions, while the aggregate trading response to revisions remains the same.
17. In a somewhat related study, Aghanya et al. (2020) study the effects of MiFID I, an earlier EU regulation enacted in 2004 that did not directly affect the sell-side analyst industry but instead increased trade transparency, investor protection and competition. They find that MiFID I reduced stock price delay, measured using the delay proxies of Hou and Moskovitz (2005).
18. This finding is complementary to the findings of Veldkamp (2005) and Brockman et al. (2010) on information production and stock comovement conditional on the business cycle.
19. Womack (1996) provides some of the first evidence of the market timing and stock picking abilities of analysts. Barber et al. (2001) show that portfolios formed from consensus recommendations yield significant abnormal returns, while the results of Jegadeesh et al. (2004) suggest that recommendation changes are a robust return predictor. Pursiainen (2022) shows European evidence of analyst recommendations predicting stock returns, albeit affected by cultural biases.
20. In the Internet Appendix, we show that our results remain qualitatively similar if we remove Swiss firms from our sample.
21. For robustness, we also consider other matching schemes. See Section 4.3 for more details.

22. The full regression results for this model are reported in column 2 of Internet Appendix Table A13.

23. We thank an anonymous referee for this suggestion.

24. We use EUROFIDAI trading data to calculate trading by venue for each stock.

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