Analyst Incentives and Stock Return Synchronicity: Evidence from MiFID II*

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Abstract

We study the role of analyst incentives in the overall information environment in the stock market, focusing on the fundamental changes brought by MiFID II on the sell-side research industry in Europe. Implemented in 2018, MiFID II substantially changed analyst incentives, forcing them to work harder to justify the value they add. We find that, while the number of analysts decreases, the average stock return synchronicity with the market also decreases, implying an imprevement in stock price informativeness. The decrease in synchronicity is larger for firms that are likely to be more important for the analysts and brokers covering them. It is also asymmetric and substantially larger for downside market movements. Similarly, stock price crash risk decreases following the introduction of MiFID II. These results indicate that both systematic and idiosyncratic downside risk decrease. We also find that consensus earnings estimates become more accurate following MiFID II. Our results suggest that, by changing incentives, MiFID II not only improves the quality of individual analyst work, as reported by prior studies, but also achieves an improvement in the aggregate information environment with fewer analysts producing this information.

JEL classification: G14, G15, G18, G24

Keywords: Stock return synchronicity, sell-side analysts, crash risk, MiFID II

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1 Introduction

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 (see, e.g., Harford, Jiang, Wang, and Xie, 2019). By implication, changes in the structure of the sell-side analysis market are likely to have important consequences for price informativeness. In January 2018, the European Union implemented a fundamental change in the market for sell-side analysis, in the form of the Markets in Financial Instruments Directive II (MiFID II). MiFID II requires asset managers and broker-dealers to unbundle the cost of equity research from trade execution costs and to justify how external research contributes to making better investments. The transparency introduced by MiFID II forces equity analysts to clearly justify their value and hence fundamentally changes the incentives and the nature of competition.

At the aggregate level, MiFID II has two broad effects that are likely to have different implications for stock price informativeness. 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. Both of these effects have been documented by prior literature. However, these studies primarily focus on the incentive effect on individual analysts. For example, both Guo and Mota (2020) and Fang, Hope, Huang, and Moldovan (2020) find that the number of sell-side analysts covering European firms decreases, but average research quality improves. Lang, Pinto, and Sul (2019) argue that the increase in individual analyst effort is not enough to offset the reduction in quantity, and hence that aggregate information environment deteriorates. However, none of these prior studies directly assesses the aggregate information environment in the market. Given the simultaneous decrease in quantity but increase in quality of equity research, it is not clear whether MiFID II should improve or reduce aggregate stock price informativeness.

In this paper, we take a different approach to looking at the impact of MiFID II, by studying its impact on stock price informativeness directly. In effect, we ask whether the net impact of the decrease in quantity and the increase in quality of information is positive of negative on aggregate stock price informativeness. 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 to not only focus on what happens at the individual analyst level, but to also try to undestand what happens to the market at the aggregate level.

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.[1] We measure stock price informativeness by stock return synchronicity, calculated as the correlation of daily stock returns with the market index. To make sure our findings are not driven by general changes in the equity markets, we construct a propensity-score-matched control group using the universe of U.S. listed firms and compare our European sample against these firms. For every European firm, we pick the closest U.S. firm based on size, book-to-market ratio, past return, and analyst coverage. We focus on the period from 2015 to 2019 and compare stock price informativeness in the years before MiFID II to that after it. We define the years from 2017 onwards as post-MiFID II, even though officially the directive came into force in January 2018. The reason is that most of the structural changes taking place in the market appear to happen already ahead of implementation (Fang et al., 2020). The largest reduction in European analyst numbers takes place in 2017.

We find that the introduction of MiFID II is associated with a significant reduction in stock return synchronicity, suggesting that stock prices become more informative. Relative to the U.S. control group, the 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

[1] 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 that this limitation does not materially change our findings.

correlation between European and U.S. firms in the pre-MiFID II period in 2015-2016. This result suggests that the stock price informativeness of European firms significantly increases following the MiFID II implementation.

If the impact of MiFID II is driven by a change in analyst incentives, we might expect it to have a larger effect for firms that are more important for 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 rankings to measure the importance of a firm to an analyst, as well as a similar measures for the broker. We also calculate adjusted versions of these measures, adjusting the market capitalizations by the number of analysts covering the firm. Finally, we look at the quality of the analysts covering the firms, based on the average precisionn 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. This finding suggests that increasing analyst effort generally increases price informativeness, and the increase is larger for the firms where analysts spend the most effort.

To gain further insight into the effects of the reform, we also study stock return synchronicity during market up days and market down days. This analysis is motivated by the findings of Ang, Chen, and Xing (2006) and Huang, Jiang, Liu, and Liu (2020), who observe that there may be differences in market correlations depending on market conditions. Specifically, we divide the days in each year into two parts – those above (up days) and those below (down days) median market return – and study the market correlation separately for these up and down days. We find that impact of MiFID II is, indeed, asymmetric depending on market condtions. Our results show that stock return synchronicity decreases significantly more during market down days than during market up days. This asymmetric effect is also statistically and economically significant, with downside correlation decreasing by more than

5 %-points more than upside correlation. This suggests that stock prices appear to comove less with downside market movements, making stock prices less contagious to negative shocks and reducing market fragility.

Following the observation of asymmetric synchronicity during market down-days and up-days, we also perform an analysis of stock price crash risk. Based on prior literature, we construct three standard measures of stock price crash risk, including negative skewness, down-to-up volatility, and extreme sigma (e.g., Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011; Callen and Fang, 2015; Kim, Li, Lu, and Yu, 2016; Andreou, Louca, and Petrou, 2017). Based on all of these measures, MiFID II implementation is associated with a significant reduction in stock price crash risk.

Taken together, our findings on the conditional stock return synchronicity and stock price crash risk suggest that both systematic and idiosyncratic downside risk decrease following MiFID II implementation. Stock prices become less prone to downward moves that are not justified by firm fundamentals and possibly driven by market moves. These findings are somewhat similar in spirit to the stock price fragility studied by Greenwood and Thesmar (2011), although somewhat differently defined. They define "fragility" as the susceptibility to non-fundamental shifts in demand and study the implications of common ownership or common liquidity shocks on such fragility. They also show that there is a relationship between fragility and stock co-movement, although they do not separate the upside and downside correlation.

Finally, we also test directly whether the information embedded in consensus earnings estimates improves. We find that consensus forecast errors decrease significantly amid MiFID II. This decrease is larger for positive forecast errors, while negative forecast errors also decrease in magnitude, although the latter change is not statistically significant. These results are consistent with our other findings that the aggregate information environment improves following MiFID II.

Our study contributes to several strands of literature. First, we add to the literature on equity analysts and the information that they generate, documenting the importance of market structure and incentives in the sell-side analyst industry. Second, we contribute to the literature on stock price informativeness, showing that regulatory reforms can have significant implications on market-wide stock price informativeness. Third, our findings are related to studies of market fragility, suggesting that institutional structure may be an important determinant of market fragility. Finally, we add to the literature discussing the effects of MiFID II specifically. Our findings represent a novel addition to this literature, as existing studies tend to be at the level of individual analysts, documenting that individual effort and accuracy improves while the number of analysts decreases.

Our findings are also highly policy-relevant for assessing the successfulness of the MiFID II framework adopted by the EEA. Our preliminary results suggest that this reform not only achieved stronger incentives and hence more individual effort by analysts, but also seemingly improved the overall information environment while reducing the number of analysts producing that 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.

2 Literature review

2.1 The role of analysts in information production

Sell-side equity analysts are finance professionals meant to perform fundamental analysis of companies and industries, thereby helping investors to make informed decisions and the market to allocate capital efficiently. There is evidence of useful information content in analyst recommendations. Womack (1996) provides some of the first evidence of the market timing and stock picking abilities of analysts. Barber, Lehavy, McNichols, and Trueman (2001) show that portfolios formed from consensus recommendations yield significant abnormal returns, while the results of Jegadeesh, Kim, Krische, and Lee (2004) suggest that recommendation changes are a robust return predictor.

A large related strand of literature studies the biases introduced into equity analysis by conflicts of interest. These can result from investment banking relationships (e.g., Lin and McNichols, 1998; Bradley, Jordan, and Ritter, 2003; Ljungqvist, Marston, and Wilhelm, Jr., 2006; Ljungqvist, Marston, Starks, Wei, and Yan, 2007), affiliated mutual fund holdings (Mola and Guidolin, 2009; Firth, Lin, Liu, and Xuan, 2013), or analyst career concerns (e.g., Hong, Kubik, and Solomon, 2000; Hong and Kubik, 2003; Jackson, 2005). Affiliated analysts appear to issue worse recommendations (Michaely and Womack, 1999; Barber, Lehavy, and Trueman, 2007), while competition can reduce the effects of biases in equity analysis (Hong and Kacperczyk, 2010; Merkley, Michaely, and Pacelli, 2017). Harford et al. (2019) show that analysts direct their effort strategically into the most important firms they cover, driven by personal career concerns.

2.2 MiFID II, equity analysts, and information

MiFID II requires asset managers and broker-dealers to unbundle the cost of equity research from trade execution costs and to justify how external research contributes to making better investments. This is a large shift from the earlier system, where brokerage fees were opaque and typically included a number of services bundled together, including equity research. This means that analysts now face much more competitive pressure and need to justify their fees directly to the asset managers buying the research. Liu and Yezegel (2020) provide evidence that MiFID II is indeed 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.

A number of recent studies suggest that the average quality of the information produced by sellside analysts increased amid the implementation of MiFID II. Fang et al. (2020) find that the number of sell-side analysts covering European firms decreases, particularly for firms that are less important to the sell-side, but average research quality improves. Guo and Mota (2020) document similar findings and also note that part of the improvement comes from lowquality analysts dropping out. They conclude that "selling information separately improves information quality at the cost of reducing information quantity." Similarly, based on stock price reactions to analyst forecast revisions, Lang et al. (2019) argue that the increase in individual analyst effort is not enough to offset the reduction in quantity, and hence that aggregate information environment deteriorates.

While conventional wisdom suggests that analysts produce firm-sepecific information and hence would be expected to increase firm-specific inforamtion in stock prices, the empirical evidence of this is not conclusive. Chan and Hameed (2006) find that emerging-markets securities which are covered by more analysts exhibit higher stock return synchronicity. Piotroski and Roulstone (2004) make a similar finding using U.S. data. However, neither of these studies accounts for the fact that analyst coverage is endogenously determined. Using coverage initiations, Crawford, Roulstone, and So (2012) show that adding analysts to already covered firms increases the stock price informativeness, suggesting that these analysts produce firm-specific information.

2.3 Stock price informativeness

Stock price informativeness can have important real consequences. Chen, Goldstein, and Jiang (2007) show that the amount of private information in stock price has a strong positive effect on the sensitivity of corporate investment to stock price. This suggests that firm managers can learn from the private information in stock price about their own firms fundamentals and incorporate this information in the corporate investment decisions. Similarly, Foucault and Gehrig (2008) study cross-listed firms and find that a cross-listing enables firms to obtain more precise information about the value of their growth opportunities, and that cross-listed firms make better investment decisions and trade at a premium as a result. Fresard (2012) finds that corporate savings are more sensitive to stock price when the price contains more information that is new to managers, while the results of De Cesari and Huang-Meier (2015) suggest that information in stock prices impacts quarterly dividend changes.

A number of studies have focused on the effects of firm- and market-level changes on price informativeness. For example, Haggard, Martin, and Pereira (2008) find evidence suggesting that voluntary information disclosure by firms can improve stock price informativeness. Fernandes and Ferreira (2009) find that the enforcement of insider trading laws improves price informativeness, as measured by firm-specific stock return variation, but this increase is concentrated in developed markets. Han, Tang, and Yang (2016) show theoretically that, in a setting with endogenous information, public information can harm information aggregation both through crowding out private information and through attracting noise trading. Dasgupta, Gan, and Gao (2010) argue that transparency could actually result in higher stock return synchronicity, on the basis that if stock prices are more informative about future events, there should be less surprise caused by such events.

Aghanya, Agarwal, and Poshakwale (2020) study the effects of MiFID I, an earlier EU regulation enacted in 2004. MiFID I did not directly affect the sell-side analyst industry, but instead increased trade transparency, investor protection (by requiring investment firms to obtain "best execution" of incoming market orders) and competition (by greater opportunity to trade at venues other than the organised stock exchanges). They find that MiFID I increases stock price informativeness, and the increase is larger for countries with weaker-quality regulation.

2.4 Market fragility and stock price crash risk

Ang et al. (2006) were among the first to study upside and downside risk of the stock markets separately. They show that stocks that covary strongly with the market during market declines have high average returns, and that the relationship is not simply compensation for regular market beta.

Stock market fragility has generated some literature, although there is no consistent definition of the concept. For example, Greenwood and Thesmar (2011) define an asset to be fragile if it is susceptible to non-fundamental shifts in demand. In some studies of mutual funds, fragility is definted as the sensitivity of outflows to bad past performance (Chen, Goldstein, and Jiang, 2010). There are a number of studies about fragility related to fire sales of assets (e.g., Chernenko and Sunderam, 2020; Choi, Hoseinzade, Shin, and HassanTehranian, 2020; Huang et al., 2020).

There is also a vast literature on the determinants of stock price crash risk. The reported determinants include investor differences of opinion (Hong and Stein, 2003), opacity of financial information (Hutton et al., 2009), managerial compensation (Kim et al., 2011), religiosity (Callen and Fang, 2015), accounting standards (DeFond, Hung, Li, and Li, 2015), financial statement comparability (Kim et al., 2016), CEO age (Andreou et al., 2017), deviation of cash flow rights from voting rights (Hong, Kim, and Welker, 2017), and stock liquidity (Chang, Chen, and Zolotoy, 2017).

3 Data and methodology

3.1 Sample construction

We use the implementation of MiFID II as a natural experiment to study the effect of analyst incentives on stock price informativeness. MiFID II becomes formally effective in January 2018. However, its impact on the sell-side analyst industry begins at least one year before the official implementation. Figure 1 shows the annual reduction in the number of analysts in the entire IBES 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 exectation of the implementation of MiFID II in 2017 has already strongly affected sell-side analysts. Therefore, we define years from 2017 onwards as post-MiFID II. Our sample period is from 2015 to 2019, i.e., we include two years before and after the event in our analysis.

We construct a comprehensive sample consisting of European firms and their U.S. control firms. We obtain daily stock market data and accounting information from Compustat Global for publicly listed firms headquartered in all 31 European Economic Area countries. 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 markets are 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. We calculate all stock returns for European firms in Euros. For U.S. 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 in 2015-2016. To make sure that our results are not driven by small stocks, we delete firms within the bottom size decile.

To identify the effect of the MiFID II, we match each European firm with a U.S. control firm by propensity score matching. Specifically, the propensity score for each stock is estimated via a logit model in the pooled sample of European and U.S. firms within each 2-digit NAICS industry. In the logit model, the dependent variable is a dummy that equals one for an European firm and zero otherwise. Independent variables include market capitalizaiton, book-to-market ratio, and past return from the previous year. We select the U.S. firm with the closest propensity score and analyst coverage for each European firm in our sample. Our final sample contains 2,847 European firms. The descriptive statatistics on the distribution of firms by countries and years are reported in Appendix Table A.1.

3.2 Stock price informativeness

We use STOXX 600 (obtained from Datastream) as the European market index. We use S&P 500 as the US market index. In each calendar year, we compute stock price informativeness for each EUROPEAN (US) firm as the pairwise correlation in currency-adjusted daily returns between the firm and STOXX 600 (S&P 500). In robustness tests, we have also considered using value-weighted country indices and industry indices based on 2-digit NAICS codes. We have also considered an alternative proxy for stock price informativeness. Specifically, 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 stock price is less informative on firm-specific information.

We further explore the asymmetry in stock price informativeness during market *up* days and market *down* days. Specifically, we split all trading days in a calendar year into two groups: *up*-days and *down*-days. If the stock market return in day t is above median, day t is defined as a market *up*-day; otherwise, it is defined as a market *down*-day. We calculate the pairwise correlation of the daily returns between a firm and the market index during *down*-days (labeled as $Corr.(Down)$) and during *Up*-days (labeled as $Corr.(up)$). We construct *Corr.(Difference)*$(= Corr.(Down) - Corr.(Up))$ to capture the asymmetry in the return comovement. This method to capture the asymmetry in return comovement is similar to Huang et al. (2020) and Ang et al. (2006). It represents how much more the stock comovement with downside market movements relative to upside market movements. Therefore, it can help measure the contagion effect and fragility in stock price when facing negative market shocks. If the overall price informativeness improves in the stock market, *Corr.(Difference)* should decrease, as stock price should be more stable against negative market shocks.

3.3 Stock price crash risk

Following the literature on stock price crash risk (e.g.,Hutton et al. 2009; Kim et al. 2011; Callen and Fang 2015; Kim et al. 2016; Andreou et al. 2017, among others), we construct proxies for crash risk using weekly stock returns. Specifically, we run the following regression for each stock in each year:

$$r_{i,t} = \alpha + \beta_1 \times r_{m,t-2} + \beta_2 \times r_{m,t-1} + \beta_3 \times r_{m,t} + \beta_4 \times r_{m,t+1} + \beta_5 \times r_{m,t+2} + \epsilon_{i,t} \tag{1}$$

where $r_{m,t}$ denotes the weekly market return from week t, and $r_{i,t}$ denotes the weekly return for firm i at week t. We define the firm-specific weekly return for firm i at week t as $W_{i,t} = log(1 + \epsilon_{i,t})$. We use both the leads and the lags of the market returns to take into account nonsynchronous trading, following Scholes and Williams (1977) and Dimson (1979).

We adopt three different proxies to capture stock price crash risk. The first measure is negative skewness ($NCSKEW$), computed as the ratio of the third moment of firm-specific weekly returns over the standard deviation of firm-specific weekly returns raised to the third power, and then multiplied by 1. More specifically, for a given firm i in year j, $NCSKEW$ is defined as:

$$NCSKEW_{i,j} = -\frac{n(n-1)^{\frac{3}{2}} \sum W_{i,t}^3}{(n-1)(n-2)(\sum W_{i,t}^2)^{\frac{3}{2}}} \tag{2}$$

where $W_{i,t}$ is the weekly return for firm i at week t, and n is the total number of weeks in a year. A high $NCSKEW$ indicates a high crash risk.

The second measure is down-to-up volatility ($DUVOL$). It is calculated as the natural logarithm of the standard deviation of weekly stock returns $W_{i,t}$, during the weeks in which $W_{i,t}$ is lower than its annual means (*down* weeks), over the standard deviation of weekly-stock returns $W_{i,t}$, during the weeks in which $W_{i,t}$ is higher than its annual means (*up* weeks). More specifically, for a given firm i in year j, $DUVOL$ is defined as:

$$DUVOL_{i,j} = log[\frac{(n_u - 1)\sum_{down} W_{i,t}^2}{(n_d - 1)\sum_{up} W_{i,t}^2}] \tag{3}$$

where n_u is the number of *up* weeks and n_d is the number of *down* weeks. A high $DUVOL$ indicates a high crash risk.

Our final measure for crash risk is the extreme sigma ($ESIGMA$), computed as the negative of the worst deviation of firm-specific weekly returns from the average firm-specific weekly return divided by the standard deviation of firm-specific weekly returns (Bradshaw, Hutton, Marcus, and Tehranian 2010). More specifically, for a given firm i in year j, $ESIGMA$ is defined as:

$$ESIGMA_{i,j} = -MIN[\frac{W_{i,t} - \bar{W}}{\sigma_W}] \tag{4}$$

where $\bar{W}$ and σ_W are the mean and the standard deviation of the firm-specific weekly returns, respectively. A high $ESIGMA$ indicates a high crash risk

3.4 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 U.S. control firms. Generally speaking, after the propensity score matching process, European firms and their U.S. counterparts have similar firm characteristics. This indicates that our main results based on this PSM-matched sample is not likely driven by differences in firm characteristics. The average market correlation between European firms and their U.S. counterparts are also quite similar. The average market correlation for European firms is 29%, while the average market correlation for matched U.S. firms is 32%.

4 Main results

4.1 MiFID II and stock return synchronicity

In this section, we study the effect of analyst incentives on stock price informativeness. Specifically, we compare the market correlation for both European firms and U.S. control firms in our sample, and examine how their market correlation changes around 2017, the year in which the MiFID II effect on sell-side analysts begins.

We first plot the time-series of the average market correlations for European firms and U.S. control firms in Figure 2. Before 2017, European firms and U.S. control firms have a nearly identical level of market correlation. However, after 2017, the average market correlation for European firms drops signficiantly compared to their U.S. counterparts. The univariate analysis in Table 2 confirms the trend shown in Figure 2. Before 2017, there is no significant difference in market correlation between European firms and their U.S. counterparts (t-stat = 1.15). However, since 2017, the market correlation for European firms drops 6.6% more than their U.S. counterparts (t-stat = 14.11). Considering that both the European firms and the U.S. firms have very similar firm characteristics over our sample period, this result is not likely driven by firm characteristics. Overall, both Figure 2 and Table 2 suggest that stock price informativeness has significantly improved since 2017 for European firms, as their market correlation drop significantly.

To more formally test for the MiFID II effect, we run the following regression:

$$Correlation_{i,t} = \alpha_0 + \alpha_1 \times Europe_i \times Post_t + \alpha_2 \times Europe_i + \alpha_3 \times Post_t + \beta \times X_{i,t} + \epsilon_{i,t} \quad (5)$$

where *Correlation* is the annual correlation of daily stock returns with the market index, *Europe* indicates firms headquartered in Europe, *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, and turnover rate. We winsorize all control variables at the 1% level and standardize them to have a mean of zero and a standard deviation of one. Depending on the specification, we also include firm fixed effects, industry-year fixed effects based on two-digit NAICS codes, and firm-pair-year fixed effects, including a separate fixed effect for each pair of European firm and its matched control firm on a yearly basis.

The results are shown in Table 3. Columns 1 to 4 show that, while co-movement with market decreases for all stocks, including U.S. stocks, this decrease is significantly larger for

European stocks, as shown by the significantly negative coefficient for the $Europe \times Post$ interaction term. The estimates suggest that, compared to matched U.S. firms, European firms on average experienced about 6% decline in the market correlation after MiFID II. This result is not only statistically significant but also economically large, considering that the average correlation for all European firms is about 36% before MiFID II. In other words, the introduction of MiFID II is associated with a drop in market correlation of approximately 18%. The magnitude is also similar to what we have reported in Figure 2 and Table 2.

4.2 MiFID II and analyst incentives

If the impact of MiFID II is driven by a change in analyst incentives, we might expect it to have a larger effect for firms that are more important for 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 rankings to measure the importance of a firm to an analyst, as well as a similar measures for the broker. For each analyst (broker), we rank the firms the analyst (broker) covers based on market capitalization, and scale this ranking by the total number of firms covered by the analyst (broker).

We also calculate a modified, proportional version of this measure for both the analyst and the broker. 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 (brokers) covering them, they are even more important if there are fewer other analysts (brokers) 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.

The results, shown in Table 4 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.

4.3 Stock return synchronicity and market conditions

To gain further insight into the effect of MiFID II on the information environment, we divide our measure of stock return synchronicity into two parts: upside market correlation and downside market correlation. For each year, we equally divide all trading days into two groups: *up* days and *down* days, based on the market index. For each group, we calculate market correlation based on daily observations and run the same regression as Eq.(5) except that we replace the dependent variable with $Corr.(Up)$, $Corr.(Down)$, and *Corr.(Difference)*, i.e., the difference of market correlation between *down* days and *up* days.

The results are shown in Table 5. While stock price informativeness improves significantly (decrease in market correlation) for both up- and down-market days, the effect is more than twice as large during market down days than during market up days. Columns 5-6 show that this difference is also statistically significant. For example, after controlling for firm and industry $\times$ year fixed effects, the market correlation for European firms drops by 5.4% more during down days than during up days after the introduction of MiFID II, relative to their U.S. counterparts. This effect is also economically large, compared to what we have documented in the baseline results in Table 3. This suggests that stock prices appear to comove less with downside market movements, making stock prices less contagious to negative market shocks and hence reducing market fragility.

5 Additional analysis

5.1 Synchronicity by year

To confirm that our analysis is not simply capturing on-going 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 Table 6. The reported yearly coefficients are relative to the year 2015, which is excluded from the regression.

We see that there is no significant difference between 2016 and 2015 in any of the regression specifications. In 2017, the market correlation and decreases by approximately 4.5 %-points for European firms, relative to the matched U.S. 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 forma MiFID II implementation, slightly more then 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.

5.2 MiFID II and stock price crash risk

In Section 4.3, we documented that the introduction of MiFID II is associated with a signficant decrease in stock return synchronicity, and the effect is significantly larger for negative returns. We interpret this as a reduction in market fragility. In this section, we explore another possible manifestation of market fragility, stock price crash risk. We follow the literature and construct three standard proxies for crash risk: $NCSKEW$, $DUVOL$, and $ESIGMA$. Detailed definitions of these variables can be found in Section 3.3. We re-run our main regression in Table 3 by replacing the dependent variable with these three proxies for crash risk.

The results are shown in Table 7. In all specifications, the coefficients on $Europe \times Post$ are all significantly negative, suggesting that MiFID II is associated with a significant reduction in stock price crash risk. For example, column (2) suggest that, $NCSKEW$ on European firms drops by about 0.153 after the introduction of MiFID II, compared to their U.S. counterparts. This result is also economically sizeable, considering that the average $NCSKEW$ for European firms is about -0.007 with a standard deviation of 1.215 in our sample. In other words, this effect is about 12.6% relative to the standard deviation. The other two proxies for crash risk produce very similar results.

5.3 MiFID II and consensus forecast accuracy

Our results suggest an overall imprevement in stock price informativeness following the introduction of MiFID II. If analysts generate better-quality information, we might also expect consensus estimates to become more accurate. In this section, we test that prediction. For each earnings announcement, we calculate absolute consensus forecast error, scaled by share price. We then perform a regression analysis of absolute forecast errors before and after the introduction of MiFID II.

The results are shown in Table . The average forecast error decreases by an estimated 9-13% relative to the sample average amid MiFID II. This decrease is larger for positive forecast errors, while negative forecast errors also decrease in magnitude, although the latter change is not statistically significant. These results are consistent with our other findings that the aggregate information environment improves following MiFID II.

5.4 Alternative measures for stock return synchronicity

In our main results, we measure stock price informativeness by the annual correlation between daily stock return and daily returns from STOXX 600 (S&P 500) for European (US) firms. In this subsection, we consider five different alternative measures to show that our main results are robust to different specifications.

First, we construct value-weighted country indices for each European country. For US, we use the CRSP value-weighted daily returns. Then we measure price informativeness as the annual correlation between daily stock return and its respective country index. Second, we construct value-weighted industry indices for each first 2-digit NAICS industries for European firms and US firms. Then we measure price formativeness as the annual correlation between daily stock return and its respective industry index. Third, instead of using correlation coefficients, we regress daily stock return to its respective market index (STOXX 600 or S&P 500), country index, or industry index, and obtain the R^2s from the regressions as alternative proxies for price informativeness. We re-run the regression from Table 3 using these R^2s and find similar results.

We re-run the regression from Table 3 using these alternative proxies and report the results in Table 9. We obtain similar results from all specifications. This suggests that our main results are not subject to a particular way to measure price informativeness.

We also examine the robustness in the asymmetric stock return synchronicity documented in Table 5 using these five alternative proxies. For example, we equally divide the daily returns in each year for each country index into *up* days and *down* days using median daily return. Then we compute the correlation during down days and up days, and denote the difference as *Corr.(country diff)*. We define *Corr.(industry diff)* in a similar fashion. For the proxy using R^2 with market, we regress daily stock return to its respective market index (STOXX 600 or S&P 500) during market up days and down days, and denote the difference in *down*-R^2 and *up*-R^2 as *R-sqr (diff)*. We define *R-sqr (country diff)* and *R-sqr (industry diff)* in a similar fashion. We re-run the regression in Table 5 using these alternative proxies for the asymmetry in stock return synchronicity and report the results in Table 10. We obtain similar results as reported in Table 5.

6 Conclusion

We find evidence suggesting that the implementation of MiFID II in Europe significantly increases stock price informativeness. While a number of studies report that MiFID II increases individual analyst effort and accuracy, our analysis provides the first evidence of its effects on the aggregate information environment in the stock market. We find 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. Furthermore, we find that the decrease in stock return synchronicity is disproportionately attributable to downside market comovement. Together with our finding that stock price crash risk significantly decreases, this can be interpreted as the market becoming less fragile.

Our findings suggest that the structure of equity analyst market and the regulatory framework around it can have important implications for the aggregate information environment in the stock market. In effect, our results suggest that MiFID II achieves better information with fewer analysts.

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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 European market and U.S. market each year. We assume that analysts leave the market at each year end. For instance, we assume that the change in total number of analysts from 2014 to 2015 took place at the end of 2014.

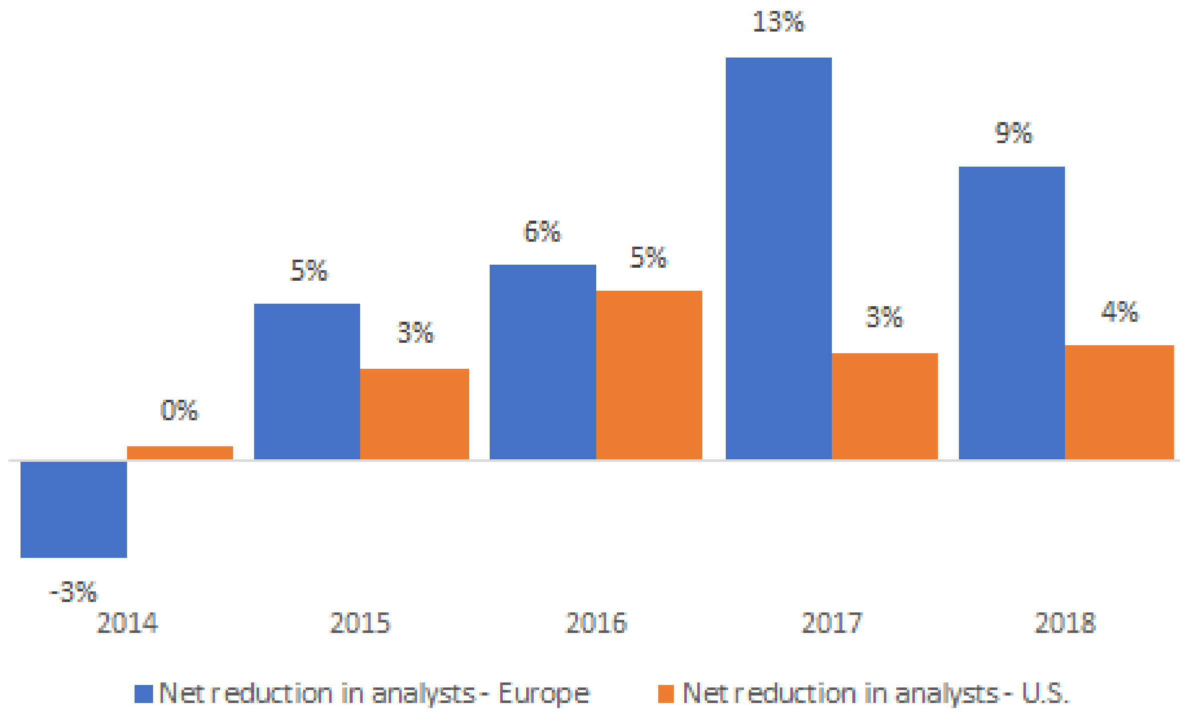

Figure 2: Correlation with Market

This figure shows the correlation with market in both Europe and U.S. each year. Correlation with market is calculated based on the daily return of each firm and the daily return of market indexes (STOXX 600 and S&P 500).

A. All European firms and matched control firms

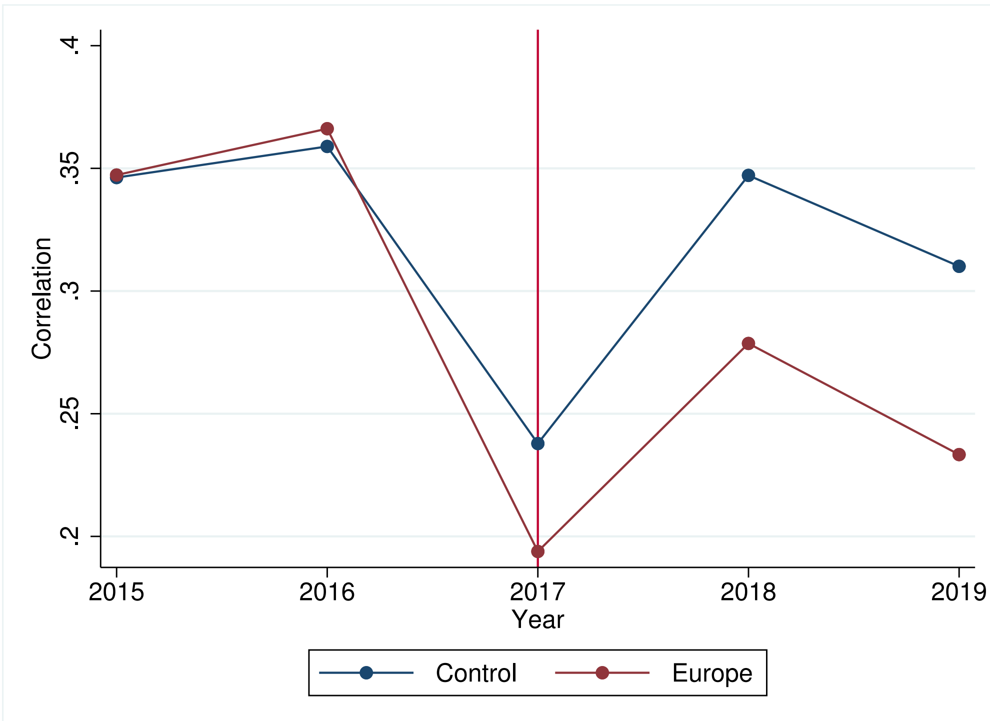

Table 1
Summary statistics

Panel A shows the summary statistics for the firm-year observations in the sample. *Correlation* is the yearly correlation coefficient of daily stock return with daily market return. *Corr.(country)* is the correlation coefficient of daily stock return with value-weighted return of all firms in each country. *Corr.(industry)* is the correlation coefficient of daily stock return with value-weighted return in each industry based on two-digit NAICS codes. *R-sqr.(market)* is the R-squared from a regression of daily stock return on daily market return. *R-sqr.(country)* is the R-squared from a regression of daily stock return on the value-weighted return of all firms in each country. *R-sqr.(industry)* is the R-squared from a regression of daily stock return on the value-weighted return of all firms in each industry based on two-digit NAICS codes. *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 of the past year. *Volatility* is the standard deviation of daily stock returns over each year. Panel B shows the comparison of summary statistics for the firm-year observations in the sample.

Panel A: European firms and matched control firms

	Mean	Std	p10	p50	p90
Synchronicity					
Correlation	0.303	0.191	0.064	0.289	0.568
Corr.(up)	0.195	0.163	-0.008	0.184	0.414
Corr.(down)	0.258	0.175	0.046	0.244	0.497
Corr.(difference)	0.063	0.136	-0.108	0.062	0.236
Corr.(country)	0.340	0.196	0.091	0.329	0.609
Corr.(industry)	0.334	0.215	0.070	0.311	0.643
R-sqr	0.128	0.134	0.005	0.084	0.322
R-sqr (country)	0.154	0.151	0.009	0.108	0.371
R-sqr (industry)	0.146	0.159	0.006	0.089	0.382
Crash risk					
NCSKEW	0.016	1.245	-1.423	-0.008	1.491
DUVOL	0.139	0.860	-0.961	0.136	1.249
ESIGMA	2.724	0.881	1.809	2.521	3.995
Firm characteristics					
Analyst coverage	7.700	8.715	1.000	4.000	22.000
Market value (EURb)	3.666	9.870	0.045	0.483	8.424
B/M	0.776	0.911	0.150	0.529	1.494
RoE	0.008	0.388	-0.276	0.083	0.241
Turnover rate	1.185	1.455	0.111	0.682	2.761
Past return	0.068	0.403	-0.390	0.035	0.528
Volatility	0.023	0.012	0.012	0.020	0.039
N	25,286				

Table 1
Summary statistics (cont'd)

Panel B: European firms vs. matched control firms

	Europe		Control (U.S.)		Europe-Control
	Mean	Std	Mean	Std	Δ Mean
Co-movement					
Correlation	0.286	0.198	0.320	0.183	0.034***
Corr.(up)	0.176	0.167	0.214	0.157	0.038***
Corr.(down)	0.256	0.181	0.261	0.169	0.005*
Corr.(difference)	0.080	0.138	0.047	0.133	-0.033***
Corr.(country)	0.348	0.207	0.332	0.184	-0.016***
Corr.(industry)	0.310	0.220	0.359	0.208	0.050***
R-sqr	0.121	0.140	0.136	0.127	0.015***
R-sqr (country)	0.164	0.168	0.144	0.130	-0.020***
R-sqr (industry)	0.144	0.169	0.148	0.148	0.004
Crash risk					
NCSKEW	-0.007	1.215	0.040	1.273	0.047**
DUVOL	0.138	0.861	0.140	0.860	0.002
ESIGMA	2.686	0.860	2.762	0.899	0.076***
Firm variables					
Analyst coverage	7.646	8.706	7.754	8.724	0.109
Market value (EURb)	3.363	9.229	3.969	10.463	0.606***
B/M	0.797	0.851	0.755	0.967	-0.041***
RoE	0.043	0.336	-0.027	0.431	-0.070***
Turnover rate	0.521	0.738	1.849	1.676	1.329***
Past return	0.058	0.392	0.079	0.414	0.021***
Volatility	0.021	0.010	0.026	0.013	0.004***
N	12,643		12,643		25,286

Table 2
Stock return synchronicity and MiFID II - univariate analysis

The average yearly *Correlation* before and after the MiFID II effect. Years 2015-2016 are defined as pre-event and years 2017-2019 as post-event. Panel A shows the univariate analysis result for all European firms and their matched U.S. control firms.

	Pre	Post	Post-Pre	t-stat
Europe	0.357	0.234	-0.123	(-36.50)
Control	0.353	0.296	-0.058	(-17.69)
Europe-Control	0.004	-0.062	-0.066	(-14.11)
t-stat	(1.15)	(-21.23)	(-14.11)	

Table 3
Stock return synchronicity and MiFID II

The dependent variable is *Correlation*, the yearly correlation coefficient of daily stock return with daily market return. *Post* is a dummy taking the value one from 2017 onwards. *Europe* is a dummy indicating firms based in Europe. Industry 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.

	(1)	(2)	(3)	(4)
Europe × Post	−0.066***	−0.064***	−0.063***	−0.064***
	(0.008)	(0.007)	(0.007)	(0.007)
Europe	0.005	0.017**		
	(0.009)	(0.007)		
Post	−0.057***	−0.066***	−0.070***	
	(0.006)	(0.005)	(0.005)	
Ln(Market value)		0.104***	0.095***	0.080***
		(0.010)	(0.013)	(0.009)
B/M		0.003	0.006*	0.003
		(0.003)	(0.003)	(0.003)
RoE		0.003	−0.002	0.000
		(0.002)	(0.002)	(0.002)
Volatility		−0.018***	−0.009**	0.002
		(0.005)	(0.003)	(0.003)
Past return		0.005**	0.005***	0.004***
		(0.002)	(0.001)	(0.001)
Turnover rate		0.009**	0.013***	0.007***
		(0.004)	(0.002)	(0.002)
Ln(1+Analyst coverage)		0.022***	0.007*	0.013***
		(0.004)	(0.004)	(0.003)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	No	No	Yes
N	25,286	25,286	25,259	25,259
R^2	0.070	0.551	0.808	0.833

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 4
MiFID II impact and firm characteristics

The dependent variable is *Correlation*, the yearly correlation coefficient of daily stock return with daily market return. *Post* is a dummy taking the value one from 2017 onwards. *Europe* is a dummy indicating firms based in Europe. *High broker importance (mcap)* is a dummy indicating whether the firm is above median in terms of its average relative ranking based on market capitalization within the broker covering it. *High analyst importance (mcap)* is the same but based on market cap rankings within the analysts instead of brokers. *High broker importance (prop. mcap)* and *High analyst importance (prop. mcap)* are based on a similar ranking but first dividing each firm's market capitalization by the number of analysts covering it. Industry 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.

	(1)	(2)	(3)	(4)	(5)
Europe x Post x High broker imp. (mcap)	−0.030***				
	(0.009)				
Europe x Post x High broker imp. (prop. mcap)		−0.029***			
		(0.007)			
Europe x Post x High analyst imp. (mcap)			−0.018**		
			(0.008)		
Europe x Post x High analyst imp. (prop. mcap)				−0.021***	
				(0.006)	
Europe x Post x High accuracy (PMAFE)					−0.015***
					(0.005)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
N	22,475	22,475	22,465	22,465	23,669
R^2	0.835	0.833	0.833	0.833	0.834

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 5
Stock return synchronicity during market up days and market down days

The dependent variable is shown above each column. *Correlation (Up)* 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 above the median. *Correlation (Down)* 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 below the median. *Correlation (Difference)* is calculated as Correlation (Down) minus Correlation (Up). Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	Corr.(Up)		Corr.(Down)		Corr.(Difference)	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	−0.042***	−0.042***	−0.095***	−0.096***	−0.053***	−0.054***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	(0.007)
Europe	−0.006		0.060***		0.066***	
	(0.005)		(0.009)		(0.006)	
Post	−0.043***		−0.047***		−0.005	
	(0.005)		(0.006)		(0.007)	
Ln(Market value)	0.085***	0.051***	0.076***	0.071***	−0.009***	0.019**
	(0.008)	(0.007)	(0.009)	(0.009)	(0.003)	(0.008)
B/M	0.003	0.009**	0.001	0.001	−0.002*	−0.008**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)
RoE	0.001	−0.001	0.001	−0.000	0.000	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Volatility	−0.012***	−0.003	−0.019***	0.003	−0.007*	0.006**
	(0.003)	(0.002)	(0.006)	(0.003)	(0.004)	(0.003)
Past return	0.003*	0.007***	0.005***	0.001	0.002	−0.006***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Turnover rate	0.002	0.004	0.008**	0.005	0.006**	0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)
Ln(1+Analyst coverage)	0.016***	0.009**	0.016***	0.010**	−0.000	0.001
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)
Firm FE	No	Yes	No	Yes	No	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes
N	25,282	25,255	25,282	25,255	25,282	25,255
R^2	0.454	0.699	0.412	0.705	0.041	0.302

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 6
Stock return synchronicity by year

The dependent variable is *Correlation*, the yearly correlation coefficient of daily stock return with daily market return. *Post* is a dummy taking the value one from 2017 onwards. *Europe* is a dummy indicating firms based in Europe. Industry 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.

	Correlation		Corr.(Difference)	
	(1)	(2)	(3)	(4)
2016 × Europe	0.002	0.003	0.018	0.015
	(0.006)	(0.006)	(0.016)	(0.016)
2017 × Europe	−0.044***	−0.045***	−0.021**	−0.024**
	(0.006)	(0.006)	(0.010)	(0.010)
2018 × Europe	−0.072***	−0.070***	−0.059***	−0.060***
	(0.007)	(0.007)	(0.013)	(0.014)
2019 × Europe	−0.077***	−0.078***	−0.058***	−0.059***
	(0.008)	(0.008)	(0.016)	(0.016)
Europe	0.016**		0.056***	
	(0.007)		(0.009)	
Ln(Market value)	0.104***	0.079***	−0.009***	0.018**
	(0.010)	(0.008)	(0.003)	(0.007)
B/M	0.003	0.003	−0.002*	−0.008**
	(0.003)	(0.003)	(0.001)	(0.003)
RoE	0.004*	0.000	0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.002)
Volatility	−0.015***	0.001	−0.004	0.006*
	(0.005)	(0.003)	(0.004)	(0.003)
Past return	0.005***	0.004***	−0.001	−0.005***
	(0.002)	(0.001)	(0.001)	(0.001)
Turnover rate	0.007*	0.007***	0.005*	0.001
	(0.004)	(0.002)	(0.002)	(0.004)
Ln(1+Analyst coverage)	0.023***	0.013***	0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.005)
Constant	0.343***	0.321***	0.030***	0.075***
	(0.010)	(0.002)	(0.007)	(0.005)
Firm FE	No	Yes	No	Yes
Industry-Year FE	No	Yes	No	Yes
N	25,286	25,259	25,282	25,255
R^2	0.571	0.833	0.081	0.305

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 7
Stock price crash risk

The dependent variable is shown above each column. *NCSKEW* is negative skewness. *DUVOL* is down-to-up volatility. *ESIGMA* is extreme sigma. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	NCSKEW		DUVOL		Extr-sigma	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	−0.170**	−0.153***	−0.149*	−0.146***	−0.070**	−0.063**
	(0.068)	(0.045)	(0.072)	(0.048)	(0.030)	(0.030)
Europe	0.153**		0.172***		0.037	
	(0.071)		(0.055)		(0.044)	
Post	0.269***		0.335***		0.105***	
	(0.045)		(0.044)		(0.020)	
Ln(Market value)	0.142***	1.884***	0.075***	1.616***	0.021	0.758***
	(0.018)	(0.097)	(0.011)	(0.099)	(0.015)	(0.055)
B/M	−0.068***	−0.058*	−0.054***	−0.041*	−0.053***	−0.017
	(0.021)	(0.032)	(0.014)	(0.024)	(0.013)	(0.018)
RoE	−0.006	−0.053*	−0.020	−0.054**	−0.018*	−0.042***
	(0.017)	(0.028)	(0.012)	(0.022)	(0.009)	(0.013)
Volatility	−0.012	−0.052*	0.042***	−0.015	−0.016	−0.100***
	(0.016)	(0.029)	(0.012)	(0.024)	(0.015)	(0.019)
Past return	0.071***	0.000	0.085***	0.002	−0.002	−0.015
	(0.018)	(0.023)	(0.015)	(0.020)	(0.009)	(0.012)
Turnover rate	0.090***	0.072***	0.059***	0.047***	0.077***	0.055***
	(0.019)	(0.021)	(0.009)	(0.015)	(0.016)	(0.015)
Ln(1+Analyst coverage)	−0.032**	−0.105**	−0.068***	−0.125***	−0.002	0.010
	(0.015)	(0.046)	(0.011)	(0.024)	(0.014)	(0.037)
Firm FE	No	Yes	No	Yes	No	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes
N	25,282	25,255	25,278	25,251	25,284	25,257
R^2	0.033	0.301	0.048	0.291	0.015	0.299

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 8
Consensus forecast error and MiFID II

The unit of observation is firm earnings announcement. The dependent variable is *Absolute forecast error*, calculated as the absolute difference between consensus EPS estimate and the actual EPS, divided by share price. To limit the impact of outlier values, the forecast error is winsorized at the 5% level before taking absolute values. The values are then scaled by the sample average. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	Full Sample		Positive FE		Negative FE	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	−0.096***	−0.068*	−0.214***	−0.159**	−0.013	−0.019
	(0.031)	(0.035)	(0.062)	(0.060)	(0.049)	(0.046)
Ln(Market value)	−0.145**	−0.750***	−0.262***	−0.957***	−0.062	−0.478***
	(0.054)	(0.092)	(0.081)	(0.129)	(0.043)	(0.069)
B/M	0.178***	0.019	0.217***	0.076**	0.156***	0.022
	(0.017)	(0.038)	(0.025)	(0.030)	(0.013)	(0.034)
RoE	−0.121***	−0.008	−0.137***	0.015	−0.101***	−0.061***
	(0.017)	(0.017)	(0.028)	(0.026)	(0.011)	(0.016)
Volatility	0.184***	0.042**	0.198***	0.065*	0.170***	0.058**
	(0.036)	(0.019)	(0.058)	(0.032)	(0.024)	(0.027)
Past return	−0.191***	−0.064***	−0.260***	−0.106***	−0.103***	−0.048**
	(0.015)	(0.012)	(0.024)	(0.025)	(0.020)	(0.017)
Turnover rate	0.002	0.014	0.022	−0.016	−0.002	0.062*
	(0.027)	(0.045)	(0.043)	(0.081)	(0.022)	(0.035)
Ln(1+Analyst coverage)	−0.098**	−0.049	−0.088	−0.085	−0.099**	0.003
	(0.041)	(0.048)	(0.062)	(0.087)	(0.036)	(0.084)
Firm FE	No	Yes	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	No	Yes	No	Yes	No
N	19,833	19,557	8,361	7,309	10,732	9,852
R^2	0.296	0.640	0.323	0.749	0.330	0.713

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 9
Alternative measures of stock return synchronicity

The dependent variable is shown above each column. *Corr.(country)* is the correlation coefficient of daily stock return with value-weighted return of all firms in each country. *Corr.(industry)* is the correlation coefficient of daily stock return with value-weighted return in each industry based on two-digit NAICS codes. *R-sqr.(market)* is the R-squared from a regression of daily stock return on daily market return. *R-sqr.(country)* is the R-squared from a regression of daily stock return on the value-weighted return of all firms in each country. *R-sqr.(industry)* is the R-squared from a regression of daily stock return on the value-weighted return of all firms in each industry based on two-digit NAICS codes. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	Corr.(country)	Corr.(industry)	R-sqr.(market)	R-sqr.(country)	R-sqr.(industry)
	(1)	(2)	(3)	(4)	(5)
Europe × Post	−0.062***	−0.061***	−0.040***	−0.052***	−0.034***
	(0.006)	(0.009)	(0.004)	(0.005)	(0.008)
Ln(Market value)	0.091***	0.093***	0.041***	0.052***	0.041***
	(0.009)	(0.009)	(0.006)	(0.007)	(0.009)
B/M	0.002	0.003	0.001	0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
RoE	0.001	0.001	−0.002	−0.001	−0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Volatility	0.003	0.003	−0.002	−0.001	−0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Past return	0.003**	0.003**	0.002***	0.002**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Turnover rate	0.008***	0.006**	0.002	0.003	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Ln(1+Analyst coverage)	0.012***	0.017***	0.004	0.004	0.004
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
N	25,234	25,073	25,259	25,234	25,073
R^2	0.833	0.867	0.806	0.823	0.850

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table 10
Alternative measures of asymmetric stock return synchronicity

The dependent variable is shown above each column. Each of them is calculated as the difference between the down- and up-synchronicity. *Corr.(country diff)* is based on the correlation coefficient of daily stock return with value-weighted return of all firms in each country. *Corr.(industry diff)* is based on the correlation coefficient of daily stock return with value-weighted return in each industry based on two-digit NAICS codes. *R-sqr.(diff)* is based on the R-squared from a regression of daily stock return on daily market return. *R-sqr.(country diff)* is based on the R-squared from a regression of daily stock return on the value-weighted return of all firms in each country. *R-sqr.(industry diff)* is based on the R-squared from a regression of daily stock return on the value-weighted return of all firms in each industry based on two-digit NAICS codes. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	Corr.(country diff)	Corr.(industry diff)	R-sqr.(diff)	R-sqr.(country diff)	R-sqr.(industry diff)
	(1)	(2)	(3)	(4)	(5)
Europe × Post	−0.054***	−0.051***	−0.040***	−0.043***	−0.048***
	(0.006)	(0.013)	(0.004)	(0.005)	(0.007)
Ln(Market value)	0.013	0.016	0.015***	0.015***	0.016***
	(0.009)	(0.010)	(0.004)	(0.005)	(0.005)
B/M	−0.007**	−0.003	−0.003**	−0.003**	−0.002
	(0.003)	(0.004)	(0.001)	(0.001)	(0.002)
RoE	0.001	0.001	−0.000	−0.000	−0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Volatility	0.007**	0.003	−0.001	0.001	0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Past return	−0.004*	−0.001	−0.002***	−0.001*	−0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Turnover rate	−0.001	−0.002	0.001	−0.001	−0.002
	(0.005)	(0.003)	(0.001)	(0.002)	(0.001)
Ln(1+Analyst coverage)	0.002	0.001	−0.001	−0.002	−0.001
	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
N	25,230	25,093	25,255	25,228	25,079
R^2	0.295	0.305	0.351	0.333	0.330

Significance levels: * 0.1, ** 0.05, * 0.01.**

A Internet appendix

A.1 Additional summary statistics

Table A.1
Summary statistics

This table shows number of firms in each country in Europe. The sample includes 2847 European firms in 30 European countries in total.

Country	Number of firms
Austria	39
Belgium	76
Bulgaria	14
Cyprus	5
Czech	5
Denmark	52
Estonia	10
Finland	82
France	350
Germany	303
Greece	30
Hungary	6
Ireland	31
Italy	158
Latvia	3
Lithuania	5
Luxembough	19
Malta	1
Netherlands	68
Poland	189
Portugal	24
Romania	14
Slovenia	8
Spain	88
Sweden	198
Norway	126
Liechtenstein	2
United Kingdom	780
Croatia	10
Switzerland	151
Toal	2847

Table A.2
Summary statistics

This table shows number of European firms included in the sample each year.

Year	Number of firms (Europe)
2015	2478
2016	2847
2017	2713
2018	2408
2019	2224

A.2 Full Europe-US sample without matching

Table A.3
Summary statistics - all European and U.S. firms

Panel A shows the summary statistics for all the firm-year observations in our full sample, which is different from the propensity score matching sample as in table 2. Panel B shows the difference in means and its significance level for each of the variables between European firms and U.S. firms. *Correlation (market)*, the yearly correlation coefficient of daily stock return with daily market return. *Analyst coverage* is the 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 of the past year. *Volatility* is the standard deviation of daily stock returns over each year.

Panel A: All European and U.S. firms

	Mean	Std	Min	p10	p50	p90	Max
Co-movement							
Correlation (market)	0.309	0.196	-0.319	0.061	0.298	0.579	0.884
Firm variables							
Analyst Coverage	8.328	8.825	0.000	1.000	5.000	21.000	66.000
Market value (EURb)	3.972	10.810	0.005	0.032	0.544	8.974	75.440
B/M	0.989	2.091	0.002	0.141	0.550	1.579	18.074
RoE	0.002	0.272	-0.792	-0.400	0.075	0.244	0.348
Turnover rate	1.367	1.691	0.016	0.116	0.794	3.178	9.907
Past return	0.044	0.424	-0.781	-0.432	0.010	0.504	1.938
Volatility	0.024	0.014	0.008	0.012	0.020	0.042	0.082
N	33,988						

Panel B: European vs U.S. firms

	Europe		US		Europe-US
	Mean	Std	Mean	Std	Δ Mean
Co-movement					
Correlation (market)	0.259	0.197	0.356	0.183	0.097***
Firm variables					
Analyst Coverage	6.734	8.275	9.797	9.059	3.062***
Market value (EURb)	2.922	8.990	4.939	12.170	2.017***
B/M	0.852	1.262	1.115	2.626	0.263***
RoE	0.029	0.246	-0.022	0.291	-0.051***
Turnover rate	0.537	0.851	2.132	1.900	1.595***
Past return	0.047	0.431	0.041	0.418	-0.006
Volatility	0.023	0.013	0.026	0.014	0.002***
N	16,295		17,693		33,988

Table A.4
Stock return synchronicity and MiFID II – all firms

The dependent variable is *Correlation (market)*, the yearly correlation coefficient of daily stock return with daily market return. Unlike as in table 4 where we only include firm-pairs using propensity score matching, all firm-year observations in Europe and U.S. with in our sample are included in this regression. *Post* is a dummy taking the value one from 2017 onwards. *Europe* is a dummy indicating firms based in Europe. Industry fixed effects are based on two-digit NAICS codes. The sample period is 2015-19. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

	(1)	(2)	(3)	(4)
Europe x Post	−0.055***	−0.049***	−0.053***	−0.048***
	(0.007)	(0.006)	(0.006)	(0.006)
Europe	−0.061***	0.051***	0.007	0.048***
	(0.013)	(0.006)	(0.007)	(0.007)
Post	−0.064***	−0.073***		
	(0.007)	(0.008)		
Ln(Market value)		0.083***	0.126***	0.076***
		(0.012)	(0.005)	(0.008)
B/M		0.004**	0.011***	0.004**
		(0.002)	(0.001)	(0.001)
RoE		0.004*	0.007***	0.005***
		(0.002)	(0.002)	(0.001)
Volatility		−0.012***	−0.008***	0.001
		(0.002)	(0.003)	(0.001)
Past return		0.004*	0.001	0.004***
		(0.002)	(0.002)	(0.001)
Turnover rate		0.014***	0.010***	0.009***
		(0.002)	(0.002)	(0.001)
Firm FE	No	Yes	No	Yes
Industry-Year FE	No	No	Yes	Yes
N	33,988	33,861	33,988	33,861
R^2	0.117	0.810	0.618	0.840

Significance levels: * 0.1, ** 0.05, * 0.01.**

Table A.5

CAR and earnings surprise. CAR is around (-1,1), winsorized at 1%, earnings surprise is defined as (actuals-consensus estimates) over share price, winsorized at 5%.

	(1)	(2)	(3)	(4)
Earnings surprise × Europe × Post	0.544**	0.529**	0.517**	0.383
	(0.213)	(0.197)	(0.197)	(0.259)
Earnings surprise × Post	−0.530**	−0.530**	−0.527**	−0.410
	(0.229)	(0.208)	(0.208)	(0.260)
Earnings surprise × Europe	−0.910***	−0.911***	−0.908***	−0.997***
	(0.255)	(0.242)	(0.243)	(0.282)
Europe × Post	0.000	−0.000	−0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.005)
Earnings surprise	1.451***	1.462***	1.460***	1.530***
	(0.304)	(0.289)	(0.289)	(0.333)
Ln(Market value)	−0.005***	−0.005**	−0.006***	−0.040***
	(0.002)	(0.002)	(0.002)	(0.010)
B/M	0.001	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
RoE	0.003**	0.003**	0.003**	−0.003
	(0.001)	(0.001)	(0.001)	(0.002)
Volatility	−0.000	−0.000	−0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Past return	−0.002**	−0.002**	−0.002**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Turnover rate	−0.002	−0.002	−0.002	−0.004
	(0.001)	(0.001)	(0.001)	(0.004)
Ln(1+Analyst coverage)	0.004**	0.004**	0.004**	0.008
	(0.002)	(0.002)	(0.002)	(0.005)
Firm FE	No	No	No	Yes
Industry-Year FE	No	Yes	Yes	Yes
Country FE	Yes	No	Yes	No
Year FE	Yes	No	No	No
Industry FE	Yes	No	No	No
N	19,833	19,834	19,833	19,557
R^2	0.044	0.054	0.056	0.319

Significance levels: * 0.1, ** 0.05, * 0.01.**