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

Yihan Li† , Xin Liu‡ , Vesa Pursiainen§

January 2021

Abstract

Implemented in 2018, MiFID II changed 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 downside 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.

JEL classification: G14, G15, G18, G24

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

*We appreciate the helpful comments from Simone Giansante, Shiyang Huang, Tse-Chun Lin, Anna Obizhaeva, Pietro Perotti, Hanwen Sun, Chi-Yang Tsou, Ru Xie, as well as seminar participants at the University of Hong Kong and conference participants at IRMC 2020, SFM 2020, ESWM 2020, HARC 2021, and Bath PhD conference 2020. We are grateful to Nasdaq Nordic Foundation for funding support. Vesa Pursiainen is grateful for the financial support from the University of Hong Kong Faculty of Business and Economics. This research was partly done during his time at University of Hong Kong. All errors are ours.

†University of Bath. E-mail: yl3696@bath.ac.uk

‡Renmin University of China. E-mail: xinl@ruc.edu.cn

§University of St. Gallen. E-mail: vesa.pursiainen@unisg.ch

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.[1]

At the aggregate level, MiFID II has two broad effects that are likely to have different implications for the information available at 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, Hope, Huang, and Moldovan (2020), Guo and Mota (2020), 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 price informativeness. Guo and Mota (2020) report that consensus forecast error decreases, suggesting an improvement in overall information. However, similar to Lang et al. (2019), they also

[1]MiFID II includes other elements as well, discussed in more detail in Section 2.

report that aggregate analyst informativeness decreases.[2] 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.[3]

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. 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 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 correlation of daily stock returns with the market index (Peng and Xiong, 2006; Huang, Huang, and Lin, 2019).[4] A higher comovement of a stock with the market reflects less firm-speficic information being incorporated into the stock price (e.g., Durnev, Morck, Yeung, and Zarowin, 2003).

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 U.S. listed

[2] 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).

[3] 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.

[4] In a robustness check analysis, we show that our results are similar when using the R^2 from a market model regression (e.g., Roll, 1988; Morck, Yeung, and Yu, 2000; Barberis, Shleifer, and Wurgler, 2005).

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.[5] 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, 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 the number of European analysts takes place in 2017.[6]

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 U.S. control group, the correlation with market decreases by more than 6 percentage 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 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.

MiFID II includes other regulatory changes that are not related to analysts. To ensure that our return synchronicity results are driven by the change in analyst incentives, and not by other changes introduced by MiFID II, we conduct a placebo test. We identify European firms whose analyst coverage decreases to zero following MiFID II. If the decrease in synchronicity is driven by analysts producing better-quality information, we should not observe a reduction in synchronicity for these firms, because they end up with no analysts to

[5]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.

[6]In the Internet Appendix, we show that our results are not sensitive to this definition of treatment timing.

produce information after MiFID II. Consistent with this conjecture, we find no reduction in stock price synchronicity for firms that lose all analysts following MiFID II. This is consistent with our main results being driven by the change in analyst incentives.

Similarly, 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. 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. 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 within-analyst market capitalization rankings to measure the importance of a firm to an analyst, as well as similar measures for the broker. We also calculate adjusted versions of these measures, adjusting market capitalization by the number of analysts covering the firm. Finally, we 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. 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.

The findings of Bris, Goetzmann, and Zhu (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. They find that in countries in which short selling is feasible and practiced, the downside-minus-upside synchronicity difference is lower, suggesting that more firm-specific negative information is incorporated. There are several reason why this might be important for the information provided by analysts. First, 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. Second, there are general differences in market correlations depending on market conditions, as observed by Ang, Chen, and Xing (2006) and Huang, Jiang, Liu, and Liu (2020), and a relative decrease in synchronicity might cause a larger absolute effect in downside 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, Liebenberg, and Schutte (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.

Motivated by these insights, and similar to Bris et al. (2007), we study the effect of MiFID II on stock return synchronicity during days of downside and upside market returns. We divide the days in each year into two parts – those above (upside days) and those below (downside days) median market return – and study stock return synchronicity separately for these. We find that the impact of MiFID II is asymmetric depending on market conditions. Our results show that stock return synchronicity decreases significantly more during downside days than during upside days. This asymmetric effect is also statistically and economically significant, with downside correlation decreasing by more than five percentage points more than upside correlation. This might suggest that stock prices incorporate more negative firm-specific information. It also implies stock prices being less contagious to negative shocks and reducing the systematic downside risk component in stock returns.

As discussed above, MiFID II entails components that are not related to analysts. Its limitations of dark pool trading volumes and increased trade transparency rules for multilateral trading facilities (MTF) 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.[7] Given MTFs include dark pools, this subsample should not be substantially affected by new rules concerning dark pools and trade transparency. We find that the decrease in synchronicity for European firms within this subsample remains similar to our full sample. This suggests that our findings are not related to the new rules for dark pool trading or MTF trade transparency.

Busch and Obernberger (2017) discuss the distinction between "information content", i.e., the amount of information incorporated into the stock price, and "price efficiency" as the degree to which all available (market-level) information is incorporated into the stock price. Our main analysis focuses on the information content part, as captured by return synchronicity with the market. However, we also study the impact of MiFID II on price efficiency.[8] Similar to Busch and Obernberger (2017), we construct three measures of price delay, first proposed by Hou and Moskowitz (2005) and used by, .e.g., Bris et al. (2007). We find that MiFID II is associated with a significant increase in price delay. In other words, the information content in stock prices increases, but price efficiency in terms of incorporating market-wide information decreases. However, this change appears to be related to the new rules regulating MTFs and not to analyst incentives. For a subsample with no MTF trading, there is no change in price delay amid MiFID II either.

Our study contributes to several strands of literature. First, we complement the literature studying the effects of MiFID II. Prior studies focus largely on the effect of MiFID II 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 is that aggregate stock price informativeness significantly improves. Second, we contribute to the vast literature on stock price informativeness, showing that regulatory reforms can have significant implications on market-wide stock price infor-

[7] We use EUROFIDAI trading data to calculate trading by venue for each stock.

[8] There is some slightly confusing use of the terminology in the prior literature. Aghanya, Agarwal, and Poshakwale (2020) study the effects of MiFID I, an earlier EU regulation enacted in 2004, and use the delay proxies of Hou and Moskowitz (2005) but discuss these as measures of "price informativeness". This interpretation is somewhat at odds with the interpretation of Hou and Moskowitz (2005), Busch and Obernberger (2017), and other studies using these measures.

mativeness. Third, our findings on the asymmetric effect of MiFID II on return synchronicity are novel in both the stock price informativeness literature as well as well as the literature on MiFID II specifically. We show that the information environment can have a differential effect on downside and upside return synchronicity. 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.

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 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.

2 Overview of MiFID II

"MiFID II/MiFIR entered into force on 3 January 2018. This new legislative framework will strengthen investor protection and improve the functioning of financial markets making them more efficient, resilient and transparent."

– *European Securities and Markets Authority (ESMA)*

In January 2018, the European Union implemented the Markets in Financial Instruments Directive II (MiFID II). This regulation represents the main reform of European financial markets regulation following the financial crisis. The aim of MiFID II is to make financial markets in Europe safer, more transparent and more resilient, as in the above quote from ESMA. This regulation followed and amended MiFID I, adopted in 2007, which sought to create a single market for investment services and activities and to ensure a high degree of harmonised protection for investors in financial instruments. MiFID II was meant to focus on the perceived shortcomings of the original MiFID and respond to the lessons learned during the financial crisis. It includes provisions related to i) conduct of business and organisational requirements for investment firms, ii) authorisation requirements for regulated markets, iii) regulatory reporting to avoid market abuse, iv) trade transparency obligation for shares, and v) rules on the admission of financial instruments to trading.

Most of this paper focuses on the impact of MiFID II on the sell-side analyst industry. 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. Thus, 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. The other components that might conceivably affect stock price informativeness include i) the rules limiting dark pool trading volumes and ii) pre- and post-trade transparency regulations related to multi-lateral trading facilities (MTFs).

3 Literature review

3.1 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. Pursiainen (2021) shows European evidence of analyst recommendations predicting stock returns, albeit affected by cultural biases.

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.

3.2 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.

At the aggregate level, MiFID II has two broad effects that have been documented by prior literature. 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. Prior studies of the MiFID II impact primarily focus on the incentive effect on individual analysts. Fang et al. (2020), Guo and Mota (2020), and Lang et al. (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, Guo and Mota (2020) report that consensus forecast error decreases, suggesting an improvement in overall information. However, similar to Lang et al. (2019), they also report that aggregate analyst informativeness decreases, 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 (Frankel et al., 2006; Lehavy et al., 2011). Lang et al. (2019) also report that market reactions to earnings surprises increase. Both Fang et al. (2020) and Lang et al. (2019) also find suggestive evidence that market liquidity decreases.

While conventional wisdom suggests that analysts produce firm-specific 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.

3.3 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 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. Huang et al. (2019) find that lower investor attention leads to higher stock comovement.

Aghanya et al. (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 decreases stock price delay, measured using the delay proxies of Hou and Moskowitz (2005).[9]

[9]Unlike Hou and Moskowitz (2005), Busch and Obernberger (2017), and other studies using these measures, Aghanya et al. (2020) argue that these measure "price informativeness". Similar to Busch and Obernberger (2017), we use the delay measures of Hou and Moskowitz (2005) as a proxy for price efficiency and comovement with market as a proxy for information content in stock prices.

Ang et al. (2006) were among the first to study the 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. Bris et al. (2007) study the comovement of stock returns with the market conditional on the direction of the market return. They find that short-selling constraints are associated with a larger difference between downside and upside comovement, implying that negative information is incorporated less efficiently. Veldkamp (2005) 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 to 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.

4 Data and methodology

4.1 Sample construction

We use the implementation 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 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 expectation 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 of European firms and match them with U.S. 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 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 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 U.S. 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 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 capitalization, book-to-market ratio, and past return from the previous year. We first select the U.S. 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.

4.2 Stock return synchronicity and asymmetry

We use STOXX 600 as the European market index and S&P 500 as the U.S. market index. For each calendar year, we compute stock return synchronicity for each European (U.S.) firm as the pairwise correlation in currency-adjusted daily returns between the firm and STOXX 600 (S&P 500). In robustness tests, we also use value-weighted country indices and industry indices based on 2-digit NAICS codes as proxies for market return, as well as R-squared in addition to correlation as an alternative measure of stock return synchronicity. In each calendar year, we regress the currency-adjusted daily returns of each European (U.S.) 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 incorporates less firm-specific information (e.g., Durnev et al., 2003).

Similar to Bris et al. (2007), we further explore the asymmetry in stock return synchronicity during upside and downside market returns. We divide all trading days in a calendar year into two groups: upside days and downside days. If the stock market return in day t is above median, day t is defined as a downside day, otherwise an upside day. We calculate the pairwise correlation of daily returns between a firm and the market index during downside days (*Corr. (Down)*) and upside days (*Corr.(Up)*). We construct *Corr.(Difference)*, calculated as *Corr.(Down)* less *Corr. (Up)*, 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).

4.3 Measures of price delay

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 quantifies how average prices adjust to it. Therefore, it is worth noting that these measures do not capture the price reaction to firm-specific information. We first estimate the base model and the extended market model as follows:

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}, \tag{1}$$

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{5} \gamma_i^n R_{m,t-n} + \varepsilon_{i,t}. \tag{2}$$

Here, $r_{i,t}$ denotes stock returns for firm i on day t, $R_{m,t}$ denotes the market return on day t, and $\varepsilon_{i,t}$ is the error term. We include five lags of market returns in the extended market model.

The first proxy for price delay ($D1$) uses the R^2s from the two above models:

$$D1 = 1 - \frac{R^2_{Base}}{R^2_{Extend}} \tag{3}$$

If market information (in terms of market return) immediately translates into a firm's stock price, the the two R^2s should be in similar magnitude, and $D1$ will be close to zero. On the other had, if there is a strong delay in the stock price incorporating market information, R^2_{Base} will be substantiallyl smaller than R^2_{Extend}, resulting in a large $D1$.

The second price delay measure ($D2$) is a coefficient ratio based on the extended market model. More specifically,

$$D2 = \frac{\sum_{n=1}^{5} n \times |\gamma_i^n|}{|\beta_i| + \sum_{n=1}^{5} |\gamma_i^n|}. \tag{4}$$

Unlike $D1$, which gives equal weights to all lags, $D2$ gives more weight to longer lags.

The final delay measure ($D3$) is a standard-error-adjusted version of $D2$. In other words, it gives more weight to more precise estimates.

$$D3 = \frac{\sum_{n=1}^{5} n \times |\gamma_i^n|/se(\gamma_i^n)}{|\beta_i| + \sum_{n=1}^{5} |\gamma_i^n|/se(\gamma_i^n}. \tag{5}$$

4.4 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 look broadly similar on most 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% over the sample period, while the average market correlation for matched U.S. firms is 32%.

5 Main results

5.1 MiFID II and stock return synchronicity

In this section, we study the effect of analyst incentives on stock return synchronicity. We compare the return synchronicities of European firms to those of the U.S. control firms and examine how they change around the implementation of MiFID II. In our analysis, 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). As shown in 1, the largest reduction in the number of European analysts takes place in 2017, as the industry adjusts ahead of MiFID II becoming effective. In the Internet Appendix Section A.5, we show that our main results remain qualitatively similar when defining the post-MiFID II period as beginning from 2018.

In Figure 2.A, we plot the average market correlations of European firms and the U.S. controls for the years 2015-2019. Before 2017, European firms and U.S. control firms have nearly identical levels of market correlation. However, after 2017, the average market correlation for European firms decreases visibly compared to their U.S. counterparts. In Figure

2.B, 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.[10] 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:

$$Correlation_{i,t} = \alpha_0 + \beta \times Europe_i \times Post_t + \gamma \times Europe_i + \theta \times Post_t + \phi \times X_{i,t} + \epsilon_{i,t}, \quad (6)$$

where *Correlation* is the annual correlation of daily stock returns with 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, 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 and industry-year joint fixed effects based on two-digit NAICS codes.

The results are shown in Table 2. 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 experience about six percentage 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%.

[10]The full regression results for this model are reported in column 2 of Table 6.

5.2 Placebo test: Firms losing all analyst coverage

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. We identify European firms whose analyst coverage decreases to zero following MiFID II. 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, because they end up with no analysts to produce such information after MiFID II. We define *Zero* as a dummy variable that equals one if a firm loses all analyst coverage following MiFID II, and zero otherwise. We re-run the regression in (6) using $Zero \times Post$, *Zero*, and *Post*.

The results are reported in Table 3. The estimated coefficient on $Zero \times Post$ is very close to zero in all specifications. It is also not statistically different from zero. This suggests that there is no reduction in synchronicity for these firms amid MiFID II, unlike for other European firms that maintain non-zero analyst coverage, as showin in Table 2. These results are consistent with our main results being driven by changes in analyst incentives.

5.3 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 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. 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.

5.4 Downside and upside 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 downside-minus-upside 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 downside and upside 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 downside 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 downside 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 during days of downside and upside market returns. 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: upside days and downside days, based on the market index. For each group, we calculate market correlation based on daily observations and run the same regression as Equation (6), except that we replace the dependent variable with $Corr.(Up)$, $Corr.(Down)$, and *Corr.(Difference)*, i.e., the difference of market correlation between downside days and upside days.

The results are shown in Table 5. While stock price informativeness improves significantly (decrease in market correlation) for both upside and downside days, the effect is more than twice as large during downside 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 percentage points more during downside days than during upside 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 downside risk component in stock returns.

6 Additional analysis

6.1 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 Table 6. The reported yearly coefficients are relative to the year 2015, which is excluded from the regression.

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 percentage 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 percentage points, and slightly further to 7.8 percentage 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.

6.2 Robustness check: Excluding stocks with MTF trading

As discussed above, MiFID II entails components that are not related to analysts. Its limitations of dark pool trading volumes and increased pre- and post-trade transparency requirements for multilateral trading facilities (MTF) might affect some of our findings. To test this, we use EUROFIDAI trading data to calculate trading by venue for each stock and repeat our main analysis for a subsample of European stocks 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 and nor MTF trade transparency requirements.

The results, shown in Table 7, remain similar to our baseline results in Table 2. The reduction in return synchronicity for firms with no MTF trading is very similar to the full sample. This suggests that our synchronicity results are not caused by the new rules for dark pool trading or MTF trade transparency.

6.3 MiFID II and price delay

Busch and Obernberger (2017) discuss the distinction between "information content", i.e., the amount of information incorporated into the stock price, and "price efficiency" as the degree to which all available (market-level) information is incorporated into the stock price. Our main analysis focuses on the information content part, as captured by return synchronicity with the market. In this section, we explore the impact of MiFID II on price efficiency. Similar to Busch and Obernberger (2017), we construct three measures of price delay, first proposed by Hou and Moskowitz (2005) and used by, .e.g., Bris et al. (2007). We then perform a regression analysis of changes in price delays amid MiFID II.

The results are shown in Panel A of Table 8. MiFID II is associated with a significant increase in price delay, suggesting that price efficiency, as measured by the speed of incorporating market-wide information, decreases. Our results also provide an interesting comparison with Aghanya et al. (2020), who study the effects of MiFID I, an earlier EU regulation enacted in 2004, and use the delay proxies of Hou and Moskowitz (2005).[11] They find that MiFID I is associated with a decrease in price delay, the opposite of our findings for MiFID II. This is not directly relevant given MiFID II was a completely separate set of regulations and did not include any new rules on sell-side analysts, but a potentially interesting contrast nevertheless.

We then study the drivers of these increases in price delay. In our main analysis, we show evidence consistent with the reduction in synchronicity being driven by the changes

[11] Aghanya et al. (2020) discuss these as measures of "price informativeness". This terminology is somewhat at odds with the interpretation of Hou and Moskowitz (2005), Busch and Obernberger (2017), and other studies using these measures.

in analyst incentives. The fact that there is no reduction for firms that retain no analyst coverage, and that the effect is similar to firms without MTF trading, suggests that the synchronicity results are not driven by dark pool- or MTF-related rules. To study whether this is also the case for the increases in price delays, we perform similar analyses focusing on i) firms completely losing analyst coverage, and ii) firms with no MTF trading.

The results are shown in Panel B of Table 8. First, the delay results are qualitatively similar for firms whose analyst coverage goes down to zero, suggesting that the price delays are unlikely related to analyst incentives. However, the price delay results disappear when only including firms with no MTF trading. This suggests that the price delay increase is more plausibly related to the new rules regulating MTFs than to changes in sell-side analyst rules. In the Internet Appendix Section A.8, we also perform an analysis of market responses to firm-specific information in the form of earnings announcements and find no increases in delay following MiFID II.

6.4 Alternative measures of stock return synchronicity

In our analyses, we measure stock return synchronicity using the annual correlation between daily stock return and daily returns of the aggregate market index.[12] 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:

- **Correlation (country):** Stock return correlation with a value-weighted market return index of its headquarter country.
- **Correlation (industry):** Stock return correlation with a value-weighted industry index return, based on 2-digit NAICS industries within Europe or U.S.

[12]We use STOXX 600 as the European market index and S&P 500 as the U.S. market index.

- **R-sqr. (market):** R^2 from a regression of daily stock return on aggregate market index.
- **R-sqr. (country):** R^2 from a regression of daily stock return on a value-weighted market index return of its headquarter country.
- **R-sqr. (industry):** R^2 from a regression of daily stock return on a value-weighted industry index return, based on 2-digit NAICS industries within Europe or U.S.
- **R-sqr. (market and industry):** R^2 from a regression of daily stock return on both the aggregate market index and a value-weighted industry index return, based on 2-digit NAICS industries within Europe or U.S.

In Panel A of Table 9, we repeat our main analysis of stock return synchronicity with each of these alternative measures as the dependent variable. The results are very similar to our main results reported in Table 2. Using any of these measures, we find that stock return synchronicity significantly decreases amid MiFID II.

In Panel B of Table 9, we also repeat our analysis of downside vs. upside stock return synchronicity with each of these alternative measures, conditional on the whether the daily market return is above or below median. These results are also similar to our main results reported in Table 5. The down-minus-up synchronicity difference decreases significantly amid MiFID II, regardless of which of these measures we use. Taken together, these results also suggest that our main results are not sensitive to a particular methodology to measure stock return synchronicity.

7 Conclusion

We find evidence suggesting that the implementation of MiFID II in Europe is associated with a significant reduction in stock return synchronicity, suggesting that more firm-specific information is incorporated in stock prices. While a number of studies report that MiFID II increases individual analyst effort and accuracy, our analysis provides the first comprehensive evidence of its effects on the aggregate information environment in the stock market. 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 findings suggest that the structure of the sell-side 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 stock price informativeness with fewer analysts. While MiFID II also seems to reduce price efficiency, as measured by delays in incorporating market-level information, this reduction appears to be more plausibly driven by new rules related to dark pools and multilateral trading facilities, not by the changes in analyst incentives. Our results suggest that the new rules on sell-side analyst industry could be viewed as having achieved better information with fewer analysts.

References

Aghanya, Daniel, Vineet Agarwal, and Sunil Poshakwale, 2020, Market in financial instruments directive (MiFID), stock price informativeness and liquidity, *Journal of Banking and Finance* 113, 1–16.

Andreou, Panayiotis C., Christodoulos Louca, and Andreas P. Petrou, 2017, CEO age and stock price crash risk, *Review of Finance* 21, 1287–1325.

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006, Downside risk, *Review of Financial Studies* 19, 1191–1239.

Barber, Brad, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? security analyst recommendations and stock returns, *Journal of Finance* 56, 531–563.

Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2007, Comparing the stock recommendation performance of investment banks and independent research firms, *Journal of Financial Economics* 85, 490–517.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–317.

Bradley, Daniel J., Bradford D. Jordan, and Jay R. Ritter, 2003, The quiet period goes out with a bang, *Journal of Finance* 58, 1–36.

Bris, Arturo, William N. Goetzmann, and Ning Zhu, 2007, Efficiency and the bear: Short sales and markets around the world, *Journal of Finance* 62, 1029–1079.

Brockman, Paul, Ivonne Liebenberg, and Maria Schutte, 2010, Comovement, information production, and the business cycle, *Journal of Financial Economics* .

Busch, Pascal, and Stefan Obernberger, 2017, Actual share repurchases, price efficiency, and the information content of stock prices, *Review of Financial Studies* 30, 324–362.

Callen, Jeffrey L., and Xiaohua Fang, 2015, Religion and stock price crash risk, *Journal of Financial and Quantitative Analysis* 1-2, 169–195.

Chan, Kalok, and Allaudeen Hameed, 2006, Stock price synchronicity and analyst coverage in emerging markets, *Journal of Financial Economics* 80, 115–147.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock price, *Review of Financial Studies* 20, 619–650.

Crawford, Steven S., Darren T. Roulstone, and Eric C. So, 2012, Analyst initiations of coverage and stock return synchronicity, *Accounting Review* 87, 1527–1553.

Dasgupta, Sudipto, Jie Gan, and Ning Gao, 2010, Transparency, price informativeness, and stock return synchronicity: Theory and evidence, *Journal of Financial and Quantitative Analysis* 45, 1189–1220.

De Cesari, Amedeo, and Winifred Huang-Meier, 2015, Dividend changes and stock price informativeness, *Journal of Corporate Finance* 35, 1–17.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, 197–226.

Durnev, Artyom, Randall Morck, Bernard Yeung, and Paul Zarowin, 2003, Does greater firm-specific return variation mean more or less informed stock pricing?, *Journal of Accounting Research* 41, 797–836.

Fang, Bingxu, Ole-Kristian Hope, Zhongwei Huang, and Rucsandra Moldovan, 2020, The effects of MiFID II on sell-side analysts, buy-side analysts, and firms, *Review of Accounting Studies* Forthcoming.

Fernandes, Nuno, and Miguel A. Ferreira, 2009, Insider trading laws and stock price informativeness, *Review of Financial Studies* 22, 1845–1887.

Firth, Michael, Chen Lin, Ping Liu, and Yuhai Xuan, 2013, The client is king: Do mutual fund relationships bias analyst recommendations?, *Journal of Accounting Research* 51, 165–200.

Foucault, Thierry, and Thomas Gehrig, 2008, Stock price informativeness, cross-listings, and investment decisions, *Journal of Financial Economics* 88, 146–168.

Frankel, Richard, S.P. Kothari, and Joseph Weber, 2006, Determinants of the informativeness of analyst research, *Journal of Accounting and Economics* 41, 29–54.

Fresard, Laurent, 2012, Cash savings and stock price informativeness, *Review of Finance* 16, 985–1012.

Guo, Yifeng, and Lira Mota, 2020, Should information be sold separately? evidence from MiFID II, *Working paper* .

Haggard, K. Stephen, Xiumin Martin, and Raynolde Pereira, 2008, Does voluntary disclosure improve stock price informativeness?, *Financial Management* 37, 747–768.

Han, Bing, Ya Tang, and Liyan Yang, 2016, Public information and uninformed trading: Implications for market liquidity and price efficiency, *Journal of Economic Theory* 163, 604–643.

Harford, Jarrad, Feng Jiang, Rong Wang, and Fei Xie, 2019, Analyst career concerns, effort allocation, and firms information environment, *Review of Financial Studies* 32, 2179–2224.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and bias, *Quarterly Journal of Economics* 125, 1683–1725.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *Journal of Finance* 58, 313–351.

Hong, Harrison, Jeffrey D. Kubik, and Amit Solomon, 2000, Security analysts' career concerns and herding of earnings forecasts, *RAND Journal of Economics* 31, 121–144.

Hong, Hyun A., Jeong-Bon Kim, and Michael Welker, 2017, Divergence of cash flow and voting rights, opacity, and stock price crash risk: International evidence, *Journal of Accounting Research* 55, 1167–1212.

Hou, Kewei, and Tobias J. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981–1020.

Huang, Shiyang, Yulin Huang, and Tse-Chun Lin, 2019, Attention allocation and return co-movement: Evidence from repeated natural experiments, *Journal of Financial Economics* 132, 369–383.

Huang, Shiyang, Wenxi Jiang, Xiaoxi Liu, and Xin Liu, 2020, Does liquidity management induce fragility in treasury prices: Evidence from bond mutual funds, *Working Paper* .

Hutton, Amy P., Alan J. Marcus, and Hassan Tehranian, 2009, Opaque financial reports, R2, and crash risk, *Journal of Financial Economics* 94, 67–86.

Jackson, Andrew R., 2005, Trade generation, reputation, and sell-side analysts, *Journal of Finance* 60, 673–717.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles M. C. Lee, 2004, Analyzing the analysts: When do recommendations add value?, *Journal of Finance* 59, 1083–1124.

Kim, Jeong-Bon, Leye Li, Louise Yi Lu, and Yangxin Yu, 2016, Financial statement comparability and expected crash risk, *Journal of Accounting and Economics* 61, 294–312.

Kim, Jeong-Bon, Yinghua Li, and Liandong Zhang, 2011, CFOs versus CEOs: Equity incentives and crashes, *Journal of Financial Economics* 101, 713–730.

Lang, Mark, Jedson Pinto, and Edward Sul, 2019, MiFID II unbundling and sell side analyst research, *Working paper* .

Lehavy, Reuven, Feng Li, and Kenneth Merkley, 2011, The effect of annual report readability on analyst following and the properties of their earnings forecasts, *Accounting Review* 86, 1087–1115.

Lin, Hsiou-wei, and Maureen F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101–127.

Liu, Zheng, and Ari Yezegel, 2020, Was MiFID II effective in unbundling execution and research services?, *Working paper* .

Ljungqvist, Alexander, Felicia Marston, Laura T. Starks, Kelsey D. Wei, and Hong Yan, 2007, Conflicts of interest in sell-side research and the moderating role of institutional investors, *Journal of Financial Economics* 85, 420–456.

Ljungqvist, Alexander, Felicia Marston, and William J. Wilhelm, Jr., 2006, Competing for securities underwriting mandates: Banking relationships and analyst recommendations, *Journal of Finance* 61, 301–340.

Merkley, Kenneth, Roni Michaely, and Joseph Pacelli, 2017, Does the scope of the sell-side analyst industry matter? an examination of bias, accuracy, and information content of analyst reports, *Journal of Finance* 72, 1285–1334.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.

Mola, Simona, and Massimo Guidolin, 2009, Affiliated mutual funds and analyst optimism, *Journal of Financial Economics* 93, 108–137.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: why do emerging markets have synchronous stock price movements?, *Journal of Financial Economics* 58, 215–260.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Piotroski, Joseph D., and Barren T. Roulstone, 2004, The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices, *Accounting Review* 79, 1119–1151.

Pursiainen, Vesa, 2021, Cultural biases in equity analysis, *Journal of Finance* Forthcoming.

Roll, Richard, 1988, R^2, *Journal of Finance* 43, 541–566.

Scholes, Myron, and Joseph Williams, 1977, Estimating betas from nonsynchronous data, *Journal of financial economics* 5, 309–327.

Veldkamp, Laura L., 2005, Slow boom, sudden crash, *Journal of Economic Theory* 124, 230–257.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137–167.

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 U.S. market each year. Analysts leave the market if they stop providing earnings estimates in IBES.

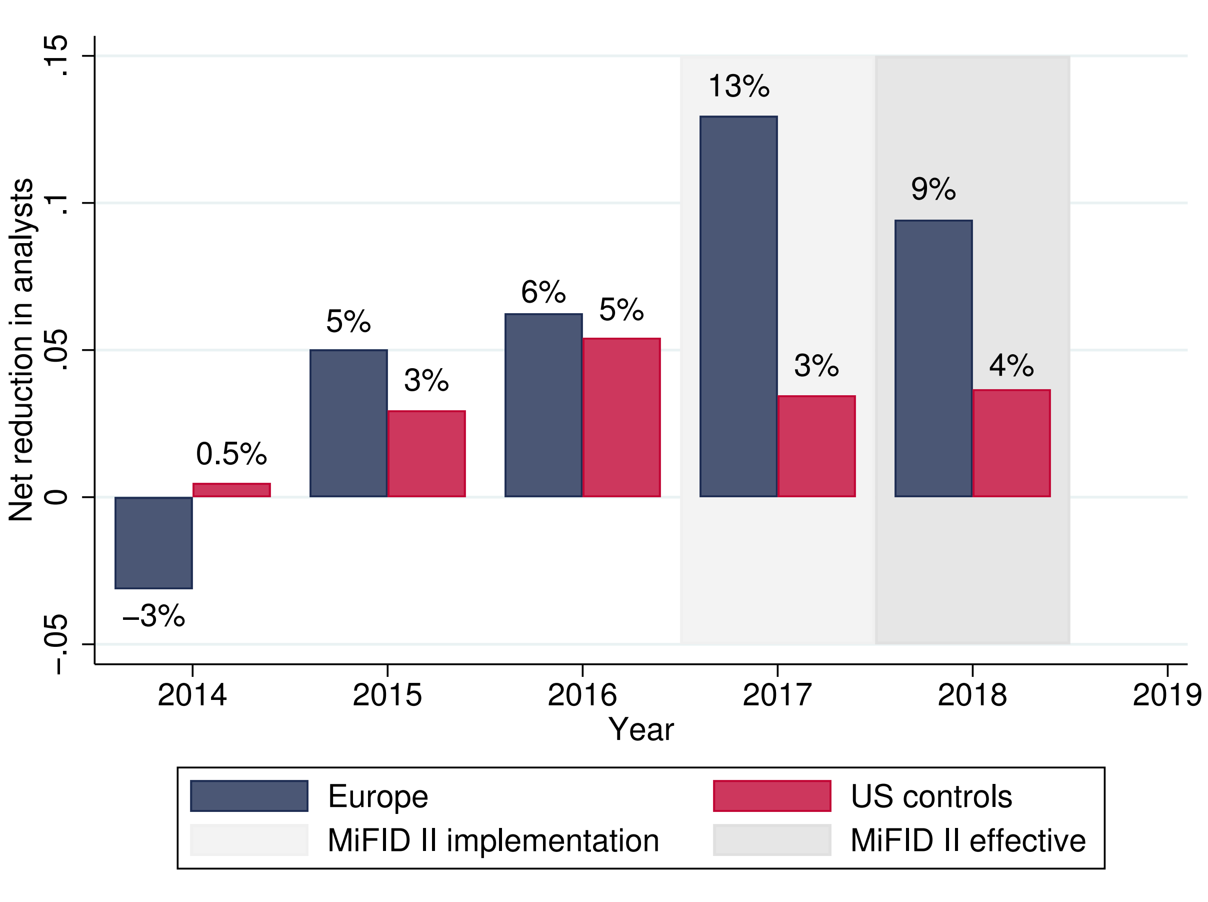


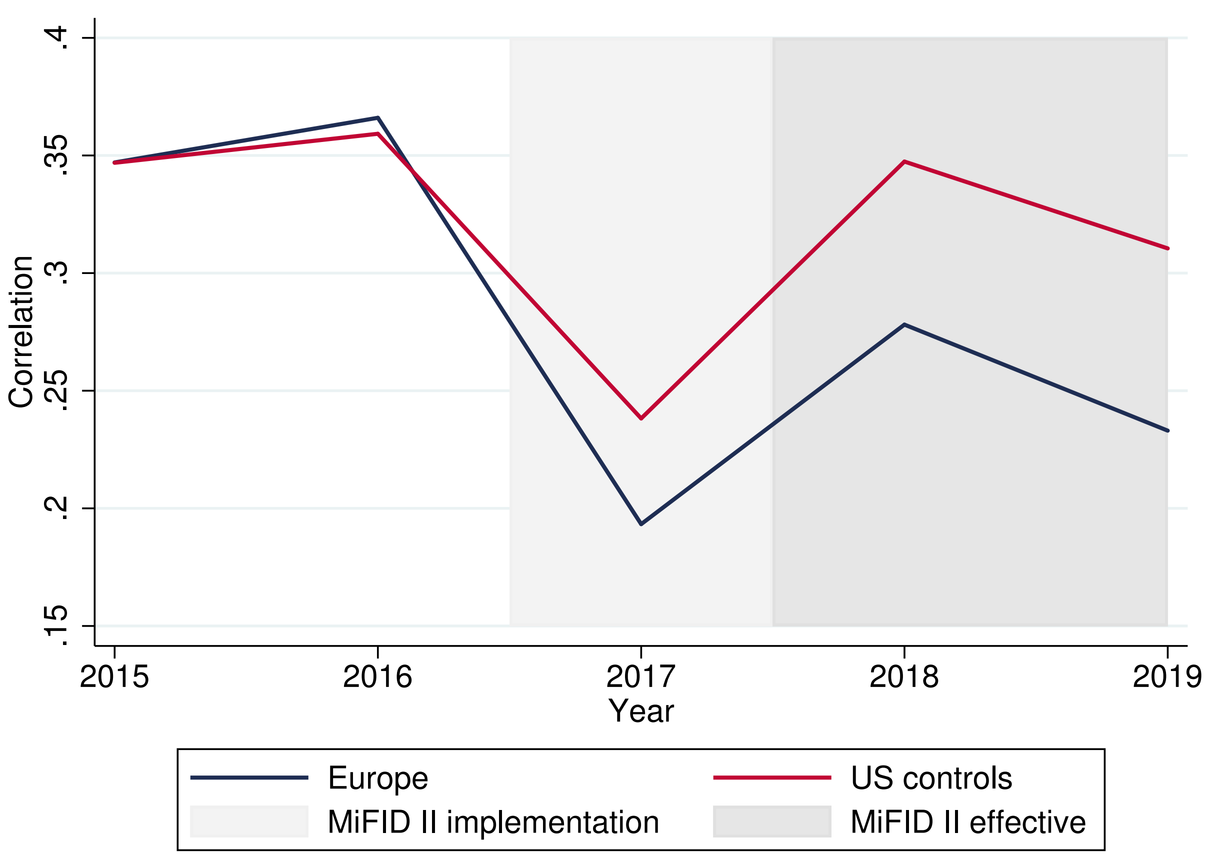
Figure 2: Return synchronicity of European firms vs. U.S. controls

Part A shows the average correlation with market for European firms and the U.S. controls each year. Part B shows the yearly coefficient estimate for *Europe* (β) from a regression specified as:

$$Correlation_{i,t} = \alpha_i + \gamma_{s(i),t} + \beta \times Europe_i \times Year + \phi \times X_{i,t} + \epsilon_{i,t}, \quad (7)$$

where i indexes a firm, t indexes a year, $s(i)$ is the industry of firm i, *Europe* is a dummy indicating whether the firm is European or a U.S. control, *Year* is a vector of year dummies, and X is a vector of controls. The excluded year interaction is 2015, so the reported coefficients are relative to 2015. Standard errors are clustered by industry.

A. Correlation with market



B. Yearly regression coefficient for Europe (relative to 2015)

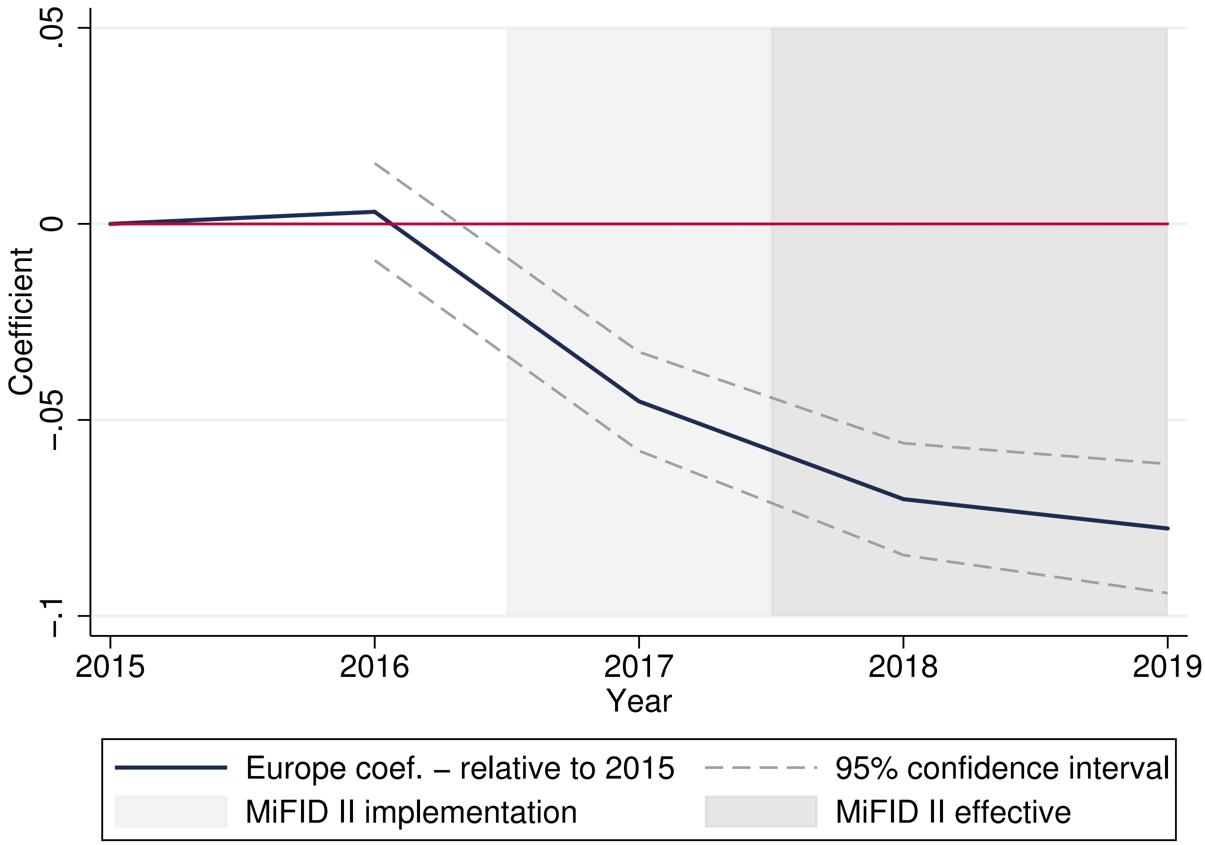


Table 1
Summary statistics

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.(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. *Corr.(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. *Corr.(Difference)* is calculated as *Corr.(Down)* minus *Corr.(Up)*. *D1, D2,* and *D3* are measures of price delay, defined in Section 4.3. *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 U.S. control firms.

Panel 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.(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)	0.064	0.136	-0.108	0.063	0.236
Price delay					
D1	0.303	0.291	0.032	0.186	0.815
D2	0.500	0.202	0.252	0.476	0.796
D3	1.472	0.651	0.711	1.368	2.366
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				

Panel B: European firms vs. matched control firms

	Europe		Control (U.S.)		Europe-Control
	Mean	Std	Mean	Std	Δ Mean
Synchronicity					
Correlation	0.285	0.198	0.320	0.183	0.035***
Corr.(up)	0.175	0.167	0.214	0.157	0.038***
Corr.(down)	0.255	0.180	0.261	0.169	0.006*
Corr.(difference)	0.080	0.138	0.047	0.133	-0.033***
Price delay					
D1	0.342	0.302	0.264	0.273	-0.077***
D2	0.527	0.207	0.473	0.194	-0.054***
D3	1.539	0.669	1.406	0.625	-0.133***
Firm characteristics					
Analyst coverage	7.621	8.674	7.728	8.694	0.107
Market value (EURb)	3.327	9.108	3.947	10.404	0.619***
B/M	0.790	0.846	0.755	0.963	-0.035**
RoE	0.042	0.337	-0.027	0.431	-0.069***
Turnover rate	0.521	0.740	1.848	1.675	1.327***
Past return	0.058	0.392	0.079	0.413	0.021***
Volatility	0.021	0.010	0.026	0.013	0.004***
N	12,540		12,540		25,080

Table 2
Stock return synchronicity and MiFID II

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.

	(1)	(2)	(3)	(4)
Europe × Post	−0.064***	−0.064***	−0.063***	−0.064***
	(0.006)	(0.007)	(0.007)	(0.007)
Europe	0.017**	0.017**		
	(0.007)	(0.007)		
Post	−0.066***		−0.070***	
	(0.005)		(0.005)	
Ln(Market value)	0.104***	0.107***	0.095***	0.080***
	(0.010)	(0.007)	(0.012)	(0.009)
B/M	0.003	0.005**	0.006*	0.003
	(0.003)	(0.002)	(0.003)	(0.003)
RoE	0.003	0.004***	−0.002	0.000
	(0.002)	(0.001)	(0.002)	(0.002)
Volatility	−0.018***	−0.011***	−0.009**	0.002
	(0.005)	(0.002)	(0.003)	(0.003)
Past return	0.005***	0.004**	0.005***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
Turnover rate	0.009**	0.006**	0.012***	0.007***
	(0.004)	(0.002)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.022***	0.025***	0.007*	0.013***
	(0.004)	(0.003)	(0.004)	(0.003)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	25,080	25,080	25,053	25,053
R^2	0.552	0.607	0.807	0.832

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

Table 3
Placebo test: Firms losing all analyst coverage

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. *Zero* is a dummy that equals one if a firm loses all analyst coverage following MiFID II, and zero otherwise. *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.

	(1)	(2)	(3)	(4)
Zero × Post	0.008	0.009	0.002	−0.001
	(0.010)	(0.010)	(0.010)	(0.009)
Post	−0.098***		−0.101***	
	(0.006)		(0.006)	
Zero	−0.043***	−0.043***		
	(0.009)	(0.009)		
Ln(Market value)	0.106***	0.109***	0.097***	0.082***
	(0.010)	(0.007)	(0.015)	(0.011)
B/M	0.003	0.005**	0.009**	0.006*
	(0.003)	(0.002)	(0.004)	(0.003)
RoE	0.002	0.003*	−0.003	−0.001
	(0.002)	(0.001)	(0.002)	(0.002)
Volatility	−0.019***	−0.011***	−0.011***	0.000
	(0.005)	(0.002)	(0.003)	(0.003)
Past return	0.006***	0.005***	0.006***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)
Turnover rate	0.014***	0.011***	0.014***	0.009***
	(0.003)	(0.002)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.019***	0.021***	0.007	0.012***
	(0.004)	(0.003)	(0.004)	(0.003)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	25,080	25,080	25,053	25,053
R^2	0.544	0.598	0.801	0.826

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 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. *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-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.

	(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***	
				(0.007)	
Europe x Post x High accuracy (PMAFE)					−0.014**
					(0.005)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
N	22,305	22,305	22,295	22,295	23,475
R^2	0.834	0.833	0.833	0.833	0.833

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

Table 5
Upside and downside return synchronicity

The dependent variable is shown above each column. *Corr.(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. *Corr.(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. *Corr.(Difference)* is calculated as *Corr.(Down)* minus *Corr.(Up)*. *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.

	Corr.(Up)		Corr.(Down)		Corr.(Difference)	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	−0.041***	−0.042***	−0.095***	−0.096***	−0.054***	−0.054***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.006)	(0.006)
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***	0.052***	0.076***	0.070***	−0.009***	0.018**
	(0.007)	(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	−0.005***
	(0.001)	(0.002)	(0.001)	(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***	0.008*	0.017***	0.010**	0.000	0.002
	(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	25,076	25,049	25,076	25,049	25,076	25,049
R^2	0.455	0.699	0.413	0.704	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 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.

	Correlation		Corr.(Difference)	
	(1)	(2)	(3)	(4)
2016 × Europe	0.002	0.003	0.020	0.017
	(0.006)	(0.006)	(0.016)	(0.015)
2017 × Europe	−0.044***	−0.045***	−0.020**	−0.024**
	(0.006)	(0.006)	(0.009)	(0.010)
2018 × Europe	−0.071***	−0.070***	−0.058***	−0.059***
	(0.007)	(0.007)	(0.013)	(0.014)
2019 × Europe	−0.076***	−0.078***	−0.058***	−0.059***
	(0.008)	(0.008)	(0.016)	(0.015)
Europe	0.015**		0.055***	
	(0.007)		(0.009)	
Ln(Market value)	0.104***	0.079***	−0.009***	0.017**
	(0.009)	(0.008)	(0.003)	(0.008)
B/M	0.002	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	0.005*
	(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***	0.012***	0.001	0.001
	(0.004)	(0.004)	(0.003)	(0.005)
Constant	0.343***	0.321***	0.031***	0.075***
	(0.010)	(0.002)	(0.007)	(0.005)
Firm FE	No	Yes	No	Yes
Industry-Year FE	No	Yes	No	Yes
N	25,080	25,053	25,076	25,049
R^2	0.572	0.833	0.081	0.305

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

Table 7
Firms with no MTF trading

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. Firms included in the sample of this test are European firms that have zero MTF trading between 2015-2019 and their U.S. matched firms. *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.

	(1)	(2)	(3)	(4)
Europe × Post	−0.057***	−0.057***	−0.056***	−0.056***
	(0.009)	(0.009)	(0.009)	(0.009)
Europe	−0.029***	−0.029***		
	(0.010)	(0.010)		
Post	−0.046***		−0.054***	
	(0.008)		(0.008)	
Ln(Market value)	0.063***	0.066***	0.068***	0.055***
	(0.007)	(0.007)	(0.014)	(0.012)
B/M	−0.001	0.003	0.009	0.009
	(0.003)	(0.002)	(0.007)	(0.006)
RoE	0.007**	0.006***	−0.000	0.001
	(0.002)	(0.002)	(0.004)	(0.003)
Volatility	−0.021***	−0.018***	0.000	0.003
	(0.005)	(0.004)	(0.002)	(0.002)
Past return	0.007***	0.005***	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Turnover rate	0.014***	0.012**	0.014***	0.013***
	(0.004)	(0.004)	(0.003)	(0.003)
Ln(1+Analyst coverage)	0.012***	0.015***	0.010**	0.016***
	(0.004)	(0.004)	(0.004)	(0.004)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	4,714	4,714	4,700	4,700
R^2	0.429	0.490	0.761	0.788

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

Table 8
Price delay and MiFID II

In Panel A, the dependent variable is shown above each column. Columns 1-3 of Panel B shows results for changes in price delay for firms whose analyst coverage falls to zero. Columns 4-6 show results for a subsample of stocks with no MTF trading. *D1*, *D2*, and *D3* are measures of price delay, defined in Section 4.3. *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.

Panel A: Price delay measures and MiFID II

	D1		D2		D3	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	0.101***	0.104***	0.063***	0.063***	0.196***	0.204***
	(0.014)	(0.013)	(0.008)	(0.008)	(0.025)	(0.024)
Europe	-0.007		0.000		-0.025	
	(0.012)		(0.008)		(0.026)	
Post	0.052***		0.041***		0.156***	
	(0.013)		(0.007)		(0.022)	
Ln(Market value)	-0.121***	-0.135***	-0.094***	-0.084***	-0.269***	-0.279***
	(0.009)	(0.019)	(0.007)	(0.012)	(0.023)	(0.041)
B/M	0.005	-0.001	0.002	-0.002	0.008	0.003
	(0.005)	(0.007)	(0.003)	(0.004)	(0.010)	(0.014)
RoE	-0.012***	-0.002	-0.006***	0.001	-0.011	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.008)	(0.006)
Volatility	0.028***	0.002	0.018***	0.001	0.065***	0.022*
	(0.008)	(0.004)	(0.005)	(0.003)	(0.019)	(0.011)
Past return	-0.016***	-0.005	-0.008***	-0.005**	-0.027***	-0.010
	(0.005)	(0.003)	(0.003)	(0.002)	(0.009)	(0.006)
Turnover rate	-0.023***	-0.017***	-0.013***	-0.009***	-0.037***	-0.028***
	(0.005)	(0.003)	(0.004)	(0.002)	(0.013)	(0.007)
Ln(1+Analyst coverage)	-0.031***	-0.034***	-0.022***	-0.019***	-0.071***	-0.052***
	(0.006)	(0.005)	(0.004)	(0.004)	(0.014)	(0.012)
Firm FE	No	Yes	No	Yes	No	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes
N	25,080	25,053	25,080	25,053	25,080	25,053
R^2	0.398	0.693	0.440	0.712	0.376	0.647

Panel B: Placebo test and zero MTF trading test

	Placebo test			No MTF trading		
	(1)	(2)	(3)	(4)	(5)	(6)
	D1	D2	D3	D1	D2	D3
Zero × Post	0.114***	0.052***	0.122**			
	(0.024)	(0.012)	(0.053)			
Europe × Post				-0.004	-0.003	-0.010
				(0.004)	(0.002)	(0.006)
Ln(Market value)	-0.136***	-0.085***	-0.283***	-0.056**	-0.028*	-0.102**
	(0.021)	(0.013)	(0.043)	(0.023)	(0.015)	(0.045)
B/M	-0.005	-0.005	-0.006	-0.027*	-0.016*	-0.049
	(0.007)	(0.004)	(0.014)	(0.015)	(0.009)	(0.031)
RoE	-0.001	0.002	0.006	-0.003	-0.002	0.004
	(0.003)	(0.002)	(0.007)	(0.006)	(0.004)	(0.013)
Volatility	0.004	0.003	0.027**	-0.007	-0.005	0.002
	(0.004)	(0.002)	(0.011)	(0.006)	(0.003)	(0.015)
Past return	-0.007**	-0.006***	-0.014**	-0.004	-0.003	0.002
	(0.003)	(0.002)	(0.006)	(0.007)	(0.005)	(0.010)
Turnover rate	-0.020***	-0.011***	-0.034***	-0.028***	-0.016***	-0.047***
	(0.003)	(0.002)	(0.008)	(0.004)	(0.002)	(0.013)
Ln(1+Analyst coverage)	-0.029***	-0.017***	-0.047***	-0.006	-0.004	-0.027
	(0.005)	(0.004)	(0.011)	(0.011)	(0.007)	(0.022)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,053	25,053	25,053	4,700	4,700	4,700
R^2	0.686	0.706	0.641	0.513	0.523	0.486

Table 9
Alternative measures of stock return synchronicity

In Panel A, 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. *R-sqr.(market and industry)* is based on the R-squared from a regression of daily stock return on the value-weighted industry return and the market return. *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. In Panel B, dependent variables are calculated in similar method.

Panel A: Alternative measures of stock return synchronicity

	Corr.(country)	Corr.(industry)	R-sqr.(market)	R-sqr.(country)	R-sqr.(industry)	R-sqr.(market and industry)
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	-0.062***	-0.061***	-0.040***	-0.052***	-0.034***	-0.034***
	(0.006)	(0.009)	(0.004)	(0.005)	(0.008)	(0.008)
Ln(Market value)	0.091***	0.093***	0.040***	0.052***	0.041***	0.051***
	(0.009)	(0.008)	(0.006)	(0.007)	(0.009)	(0.010)
B/M	0.002	0.003	0.001	0.000	0.001	0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
RoE	0.001	0.001	-0.002	-0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Volatility	0.003	0.003	-0.002	-0.001	-0.002	-0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Past return	0.003**	0.003**	0.003***	0.002**	0.003**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Turnover rate	0.008***	0.006**	0.002	0.003	0.003**	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Ln(1+Analyst coverage)	0.012***	0.017***	0.004	0.004	0.004	0.005
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,028	24,870	25,053	25,028	24,870	24,870
R^2	0.833	0.867	0.806	0.822	0.850	0.851

Panel B: Alternative measures of downside-upside synchronicity

	Corr.(ctr diff)	Corr.(ind diff)	R-sqr.(mkt diff)	R-sqr.(ctr diff)	R-sqr.(ind diff)	R-sqr.(mkt and ind diff)
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	-0.054***	-0.051***	-0.040***	-0.044***	-0.048***	-0.045***
	(0.006)	(0.013)	(0.004)	(0.005)	(0.007)	(0.010)
Ln(Market value)	0.012	0.014	0.015***	0.015**	0.015***	0.011**
	(0.009)	(0.010)	(0.004)	(0.005)	(0.005)	(0.004)
B/M	-0.007**	-0.004	-0.003**	-0.003**	-0.002	-0.003
	(0.003)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
RoE	0.001	0.001	-0.000	-0.000	-0.000	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	0.007**	0.003	-0.001	0.001	0.000	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Past return	-0.003*	-0.001	-0.002***	-0.001*	-0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Turnover rate	-0.001	-0.002	0.001	-0.001	-0.002	-0.000
	(0.005)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Ln(1+Analyst coverage)	0.002	0.002	-0.001	-0.002	-0.001	-0.002
	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,024	24,890	25,049	25,022	24,876	24,863
R^2	0.295	0.306	0.350	0.333	0.331	0.310

A Internet appendix

A.1 Additional summary statistics

Table A.1
Summary statistics

This table shows the number of firms in each country in Europe. The sample includes 2817 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	349
Germany	286
Greece	30
Hungary	6
Ireland	31
Italy	157
Latvia	3
Lithuania	5
Luxembough	18
Malta	1
Netherlands	67
Poland	189
Portugal	24
Romania	14
Slovenia	8
Spain	88
Sweden	198
Norway	126
Liechtenstein	2
United Kingdom	775
Croatia	9
Switzerland	148
Toal	2817

Table A.2
Summary statistics

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

Year	Number of firms (Europe)
2015	2452
2016	2817
2017	2687
2018	2384
2019	2200

A.2 Full Europe-U.S. sample without matching

In our main analysis, we use a sample of European firms and mathed U.S. control firms. To make sure that our results are not driven by the control group matching methodology or other sample limitations, in this section, we include all European firms in our sample as well as all U.S. firms, without any matching or limitations. Table A.3 shows the summary statistics for this sample.

Table A.4 shows regression results of return synchronicity around MiFID II. The results are very similar to our main results using the matched control sample. This suggests that our results are not substantially affected by the matching methodology.

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

Panel A shows the summary statistics for all European and U.S. firms, without any control group matching. 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
Synchronicity							
Correlation (market)	0.308	0.195	-0.319	0.061	0.296	0.577	0.884
Firm variables							
Analyst coverage	8.328	8.831	0.000	1.000	5.000	21.000	66.000
Market value (EURb)	3.955	10.837	0.005	0.032	0.536	8.829	75.659
B/M	0.872	1.427	0.001	0.141	0.545	1.528	11.916
RoE	0.002	0.272	-0.795	-0.403	0.075	0.243	0.347
Turnover rate	1.347	1.660	0.016	0.116	0.784	3.127	9.728
Past return	0.044	0.425	-0.782	-0.433	0.010	0.505	1.942
Volatility	0.025	0.014	0.008	0.012	0.021	0.042	0.082
N	33,676						

Panel B: European vs U.S. firms

	Europe		US		Europe-US
	Mean	Std	Mean	Std	Δ Mean
Synchronicity					
Correlation (market)	0.259	0.197	0.354	0.182	0.096***
Firm variables					
Analyst coverage	6.734	8.275	9.823	9.071	3.088***
Market value (EURb)	2.923	9.001	4.923	12.233	2.000***
B/M	0.839	1.116	0.902	1.666	0.063***
RoE	0.029	0.247	-0.024	0.292	-0.053***
Turnover rate	0.537	0.844	2.107	1.864	1.570***
Past return	0.047	0.431	0.041	0.419	-0.006
Volatility	0.023	0.013	0.026	0.014	0.002***
N	16,295		17,381		33,676

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. We include all European and U.S. firms, without any control group matching. *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.

	(1)	(2)	(3)	(4)
Europe x Post	−0.056***	−0.050***	−0.054***	−0.050***
	(0.007)	(0.006)	(0.006)	(0.006)
Europe	−0.059***		0.008	
	(0.013)		(0.007)	
Post	−0.063***	−0.072***		
	(0.007)	(0.008)		
Ln(Market value)		0.085***	0.126***	0.078***
		(0.013)	(0.005)	(0.009)
B/M		0.005**	0.008***	0.004*
		(0.002)	(0.001)	(0.002)
RoE		0.004*	0.007***	0.005***
		(0.002)	(0.002)	(0.001)
Volatility		−0.012***	−0.009***	0.001
		(0.002)	(0.003)	(0.001)
Past return		0.004*	0.001	0.005***
		(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	33,676	33,549	33,676	33,549
R^2	0.115	0.811	0.617	0.841

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

A.3 MiFID II and stock price crash risk

In Section 5.4, we document that the introduction of MiFID II is associated with a signficant decrease in stock return synchronicity, and the effect is significantly larger for downside returns. This can be interpreted as a reduction in exposure to systematic downside risk. In this section, we explore an idiosyncratic component of downside risk, stock price crash risk.

Following the literature, we construct three commonly used proxies for crash risk using weekly stock returns: negative skewness, down-to-up volatility, and extreme sigma (see, 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; Hong, Kim, and Welker, 2017). For calculating these measures, we first perform the following regression for each stock in each year:

$$r_{i,t} = \alpha + \beta_1 \times r_{m,t-2} + \beta_2 \times r_{m,t-1} + \beta_3 \times r_{m,t} + \beta_4 \times r_{m,t+1} + \beta_5 \times r_{m,t+2} + \epsilon_{i,t} \qquad (8)$$

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 $W_{i,t} = ln(1 + \epsilon_{i,t})$. 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).

The first crash risk measure, negative skewness ($NCSKEW$), is 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 minus one:

$$NCSKEW_{i,j} = -\frac{n(n-1)^{\frac{3}{2}} \sum W_{i,t}^3}{(n-1)(n-2)(\sum W_{i,t}^2)^{\frac{3}{2}}} \qquad (9)$$

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, down-to-up volatility ($DUVOL$), 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):

$$DUVOL_{i,j} = log[\frac{(n_u - 1)\sum_{down} W_{i,t}^2}{(n_d - 1)\sum_{up} W_{i,t}^2}] \tag{10}$$

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 third measure for crash risk, extreme sigma ($ESIGMA$), is computed as the negative of the largest negative deviation of firm-specific weekly returns from the average firm-specific weekly return divided by the standard deviation of firm-specific weekly returns:

$$ESIGMA_{i,j} = -MIN[\frac{W_{i,t} - \bar{W}}{\sigma_W}] \tag{11}$$

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

We then re-run our main regression in Table 2, replacing the dependent variable with these three proxies for crash risk. The results are shown in Table A.5. 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 decreases by about 0.153 after the introduction of MiFID II, compared to the U.S. control firms. This result is also economically sizeable, equivalent of about 12.6% of the standard deviation. The other two proxies for crash risk produce very similar results.

Table A.5
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. 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. parentheses.

	NCSKEW		DUVOL		Extr-sigma	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	−0.174**	−0.157***	−0.153**	−0.149***	−0.071**	−0.064**
	(0.067)	(0.045)	(0.071)	(0.048)	(0.030)	(0.030)
Europe	0.156**		0.175***		0.038	
	(0.071)		(0.055)		(0.044)	
Post	0.273***		0.339***		0.108***	
	(0.044)		(0.043)		(0.020)	
Ln(Market value)	0.141***	1.882***	0.074***	1.612***	0.021	0.757***
	(0.019)	(0.099)	(0.011)	(0.099)	(0.015)	(0.056)
B/M	−0.070***	−0.055*	−0.054***	−0.039	−0.053***	−0.015
	(0.021)	(0.031)	(0.014)	(0.022)	(0.013)	(0.017)
RoE	−0.005	−0.052*	−0.020	−0.054**	−0.018*	−0.042***
	(0.017)	(0.028)	(0.012)	(0.021)	(0.009)	(0.013)
Volatility	−0.013	−0.052*	0.042***	−0.015	−0.016	−0.099***
	(0.016)	(0.029)	(0.012)	(0.023)	(0.015)	(0.019)
Past return	0.071***	0.001	0.085***	0.002	−0.003	−0.015
	(0.017)	(0.022)	(0.015)	(0.019)	(0.008)	(0.012)
Turnover rate	0.091***	0.075***	0.060***	0.049***	0.077***	0.057***
	(0.019)	(0.020)	(0.009)	(0.015)	(0.016)	(0.015)
Ln(1+Analyst coverage)	−0.033**	−0.105**	−0.067***	−0.125***	−0.003	0.011
	(0.015)	(0.047)	(0.011)	(0.024)	(0.014)	(0.038)
Firm FE	No	Yes	No	Yes	No	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes
N	25,076	25,049	25,072	25,045	25,078	25,051
R^2	0.033	0.301	0.048	0.291	0.015	0.300

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

A.4 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 A.6. 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 (i.e., consensus estimate is higher than the actual), 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.

Table A.6
Consensus forecast error and MiFID II

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, *Absolute forecast error* is winsorized at the 5% level before taking absolute values. The values are then scaled by the sample average. *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.

	Full Sample		Positive FE		Negative FE	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	−0.097***	−0.066*	−0.212***	−0.150**	−0.013	−0.019
	(0.032)	(0.036)	(0.062)	(0.059)	(0.049)	(0.045)
Europe	0.365***		0.479***		0.278***	
	(0.041)		(0.055)		(0.050)	
Post	0.011		0.088		−0.049	
	(0.030)		(0.054)		(0.052)	
Ln(Market value)	−0.137**	−0.754***	−0.269***	−0.958***	−0.045	−0.481***
	(0.056)	(0.093)	(0.082)	(0.128)	(0.043)	(0.068)
B/M	0.210***	0.018	0.253***	0.074**	0.188***	0.023
	(0.019)	(0.038)	(0.030)	(0.030)	(0.012)	(0.034)
RoE	−0.125***	−0.009	−0.137***	0.012	−0.111***	−0.062***
	(0.018)	(0.017)	(0.029)	(0.026)	(0.010)	(0.016)
Volatility	0.171***	0.040*	0.178**	0.058	0.161***	0.059**
	(0.040)	(0.020)	(0.063)	(0.034)	(0.025)	(0.027)
Past return	−0.178***	−0.064***	−0.246***	−0.103***	−0.095***	−0.049***
	(0.016)	(0.012)	(0.025)	(0.024)	(0.018)	(0.017)
Turnover rate	0.001	0.014	0.019	−0.018	−0.002	0.062*
	(0.033)	(0.045)	(0.051)	(0.083)	(0.026)	(0.035)
Ln(1+Analyst coverage)	−0.103**	−0.049	−0.071	−0.093	−0.109**	0.006
	(0.045)	(0.048)	(0.066)	(0.087)	(0.039)	(0.084)
Firm FE	No	Yes	No	Yes	No	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes
N	19,665	19,390	8,294	7,246	10,647	9,771
R^2	0.270	0.640	0.287	0.750	0.287	0.713

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

A.5 Alternative definition of treatment timing

Although the sell-side analyst industry has started to experience a dramatic structural change since 2017, the official implementation of MiFID II, MiFID II starts from the first trading day of 2018. To show that our results are not driven by using 2017 as the event year, we re-examine our baseline result using 2018 as the event year. A.7 shows that our main results remain robust under this alternative specification.

Table A.7
Treatment timing as 2018 onwards

The dependent variable is *Correlation*, the yearly correlation coefficient between daily stock returns and daily market returns. *Post(2018)* is a dummy that equals one from 2018 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.

	(1)	(2)	(3)	(4)
Europe × Post(2018)	−0.059***	−0.059***	−0.059***	−0.059***
	(0.006)	(0.006)	(0.006)	(0.006)
Europe	0.001	0.001		
	(0.006)	(0.006)		
Post(2018)	0.006*		0.010**	
	(0.003)		(0.003)	
Ln(Market value)	0.098***	0.107***	0.017*	0.079***
	(0.010)	(0.007)	(0.009)	(0.008)
B/M	0.003	0.005***	0.000	0.003
	(0.003)	(0.002)	(0.003)	(0.003)
RoE	0.003	0.003**	0.003**	−0.000
	(0.002)	(0.001)	(0.001)	(0.002)
Volatility	−0.020***	−0.012***	−0.018***	0.000
	(0.005)	(0.002)	(0.005)	(0.003)
Past return	0.010***	0.004***	0.017***	0.005***
	(0.003)	(0.001)	(0.002)	(0.002)
Turnover rate	0.010***	0.006**	0.014***	0.008***
	(0.003)	(0.002)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.026***	0.024***	0.017***	0.012***
	(0.004)	(0.003)	(0.003)	(0.003)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	25,080	25,080	25,053	25,053
R^2	0.491	0.605	0.748	0.831

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

A.6 Price response time to earnings announcements

Our results suggest that MiFID II is associated with a significant increase in price delay, as measured by the speed of incorporating market-wide information. A nautral extension is to examine how MiFID II affects the speed of incorporating firm-specific information. In order to test this, for each earnings announcement, we calculate *price response time*, defined as the ratio of absolute CAR(0,1) over CAR(0,21), where $t = 0$ is the earnings announcement day or the ensuing trading day. Abnormal returns are computed as the difference between daily stock return and the daily market return.A.8 shows that there is no increases in the delay of firm-specific information following MiFID II.

Table A.8
Price response time to earnings announcements

The dependent variable is *price response time*, the absolute CAR (0,1) over absolute CAR(0,21). *Post* is a dummy taking the value one from 2017 onwards. *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.

	(1)	(2)	(3)	(4)
Europe × Post	0.003	0.003	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Europe	−0.018***	−0.020***		
	(0.006)	(0.006)		
Post	0.006*		0.007*	
	(0.004)		(0.004)	
Ln(Market value)	0.000	0.004*	0.022**	0.020**
	(0.002)	(0.002)	(0.010)	(0.010)
B/M	−0.009***	−0.004**	0.003	0.002
	(0.001)	(0.002)	(0.002)	(0.002)
RoE	0.010***	0.007***	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.002)
Volatility	−0.002	−0.003	0.000	−0.001
	(0.005)	(0.003)	(0.003)	(0.003)
Past return	−0.003**	−0.002*	−0.003*	−0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Turnover rate	0.010***	0.007***	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.015***	0.015***	0.008**	0.008**
	(0.003)	(0.004)	(0.003)	(0.004)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	24,120	24,120	24,067	24,067
R^2	0.064	0.101	0.403	0.412

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