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Essays on characteristics of sell-side financial analysts and information environment of financial markets

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Essays on characteristics of sell-side financial analysts and information environment of financial markets

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I am the author of this thesis, and the work described therein was carried out by myself personally, with the exception of one academic paper (Chapter 2 of this thesis) where 66% of the work was carried out by other two researchers *(formulation of ideas, design of methodology, and presentation of data in journal format).*

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Abstract

Sell-side analysts play important roles in modern financial markets, especially during the process of information production and incorporation. Therefore, characteristics of sell-side analysts and how they change the information environment of financial markets have been interesting topics to explore. In this thesis, I conduct several research to explore the roles that sell-side analysts play in the stock markets, especially during the information production and transmission process.

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

Next, I further explore how seniority of analyst teams changes the performance of sell-side analysts and analyst teams differently. I find evidence to show that analysts perform better when working in teams by using Chinese stock market data and sell-side reports from 2000 to 2021. I study the role that seniority plays in determining the performance and market impact of analyst teams and individual analysts. By double sorting on recommendation revisions direction and seniority ranking, I show that analyst teams with higher mean seniority significantly out-perform their counter parts by higher market impact and lower forecast error. But I don't observe similar phenomenon for individual analysts that work by themselves. I further enhance these results by using team-change as a direct opportunity to

study the role of senior analysts within an existing analyst team and find evidence to show that senior analysts could significantly improve the relative forecast accuracy. These results indicate that seniority plays important roles in determining the overall performance of analyst teams. It seems seniority of analysts is an important and valuable attribute in determining performance, but only kicks in when analysts work together.

Finally, I study the relationship between price informativeness and synchronicity of stock returns. The relationship between synchronicity and the level of firm-specific information incorporated into stock prices has long been under debate. In this research, I find evidence to show that lower synchronicity indicates higher amount of firm-specific information incorporated into stock prices, and therefore better stock price informativeness, by using recommendation revisions issued by sell-side analysts. I further find that synchronicity starts to decrease as early as 15 trading days before actual announcements of recommendation revisions, suggesting possible leak of valuable firm-specific information from sell-side analysts way ahead of time.

Chapter 1. Introduction

1.1. Motivation

In financial market, sell-side analysts working for brokerage firms play an important role in the process of information production. These analysts are finance professionals hired to perform fundamental and technical analysis for companies and industries, hence helping investors to make informed investment decisions, and helping the market to efficiently allocate financial resources. On one hand, sell-side analysts carefully conduct research regarding industries and firms through gathering and digesting publicly available firm disclosures and communicating with management teams as well as industry experts through conference calls and other situations. On the other hand, these analysts communicate with buy-side institutional clients regarding their recommendations and forecasts after completing their sell-side reports, thus providing valuable firm-specific and industry-wide information to the stock market. There is evidence of precious information content within analyst recommendations and sell-side reports. Womack (1996) was among the first to provide 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 revisions are robust return predictors. Important as they are, the information production process and characteristics that determine the performance of those sell-side analysts thus become interesting topics to explore in the academia.

In this research, I first examine how MiFID II, an important financial regulation implemented in European Union changes the price informativeness of European stock markets through changing the incentives of sell-side analysts. Previous literature is somewhat ambiguous regarding the aggregate changes in the information environment of European stock markets after the implementation of MiFID

II in 2018. This research aims to fill this gap.

Next, I examine the role of seniority within analyst teams by using detailed recommendation report data in Chinese stock market. The sell-side recommendation dataset provided by CSMAR contains detailed information of all team members that signed their names when publishing sell-side reports (which is different from I/B/E/S), providing an excellent opportunity to directly explore how seniority determines the performance of individual analysts and analyst teams differently.

Finally, I examine the relationship between synchronicity and price informativeness. There's an ongoing debate regarding the relationship between synchronicity of stock prices and price informativeness of stock prices, with some literature claiming lower synchronicity suggests better price informativeness and some other literature supporting the idea that lower synchronicity means worse price informativeness. I seek to provide some fresh empirical evidence from Chinese stock market to better understand this topic by studying the recommendation revisions issued by sell-side analysts.

In the next few sub-sections, I briefly introduce the main findings and key results of these three studies discussed in the previous paragraphs above.

1.2. Analyst incentives and stock return synchronicity: Evidence from MiFID II

Analyst incentives are highly important for the information environment in the stock market (see, e.g., Harford, Jiang, Wang, and Xie, 2019). Changes in analyst incentives could affect both the amount and the quality of information that is incorporated into stock prices. The Markets in Financial Instruments Directive II, also known as MiFID II, is a financial regulation implemented in Europe on the first trading day of January 2018. MiFID II brought fundamental changes to the relation between buy-side institutions and sell-side analysts since it requires the unbundling of costs of research from costs of executing trade orders. Before the implementation of MiFID II, the sell-side analysts are generally paid through “soft dollars” that are bundled with trade execution fees. After the implementation of MiFID II starting from early 2018, sell-side analysts are more pressed to justify the value they could provide to buy-side institutions because they’re now being paid in real dollars. In other words, MiFID II brought changes to the sell-side industry and analysts are more incentivized to work harder to prove how their research could help asset managers making better investment decisions.

MiFID II has brought profound changes to the sell-side industry, but it has two general effects that are very likely to yield different (or even opposite) implications at the aggregate level to the information environment of the stock market as a whole. On one hand, number of analysts covering European stock market tend to decrease after the implementation of MiFID II because of fierce competition, as documented by Fang et al. (2020) and Guo and Mota (2020). On the other hand, the quality of information that analysts produce on individual level is more likely to increase, given that analysts now have to show more effort and justify the value they could provide to their buy-side clients, as documented by Lang, Pinto, and Sul (2019). The overall impact of these two different general effects on the information environment at the aggregated level, however, is not very clear so far.

In this research, I study the overall aggregate change of information environment of European stock market as a whole by studying the synchronicity between individual stock returns and market returns. To put it in another way, I intend to directly document the changes of price informativeness after the implementation of MiFID II by measuring the changes in synchronicity. In this way, I directly study the overall net effect of decreases in number of analysts and increases in quality of research provided by the remaining sell-side analysts. This exploration of overall net effect of MiFID II on the informativeness of stock prices contributes to the existing literature and fill the unexplored gap. I believe it’s both natural and necessary to study the overall aggregate effect on firm-level when assessing MiFID II, instead of merely focusing on analyst-level proxies such as forecast errors.

My research shows that the overall price informativeness has significantly improved in European stock market following the implementation of MiFID II. I also showed that the improvement of price informativeness is directly supported by the improvement of research quality by sell-side industry. Although the implementation of MiFID II has decreased the number of analysts working in the sell-side industry, it indeed changed the incentives of analysts and encouraged them to produce higher quality reports and thus better information environment. I also show that the result documented in the main analysis (the decrease in synchronicity) after the implementation of MiFID II is asymmetric across different market conditions. I documented a larger effect during market downside days comparing to market upside days, suggesting an even larger improvement in information environment (as well as lower systematic risk) during market downside days.

I also show that idiosyncratic risks significantly decreased for European firms after the implementation of MiFID II. I then directly check the changes of analyst forecast errors by using a firm-level analysis, suggesting that sell-side industry improved the overall research quality after the implementation of MiFID II. Besides using correlation coefficient between individual stock returns and market index returns as proxy for synchronicity, I also test the main hypothesis using some other proxies for synchronicity, including the widely accepted R-squared. The results are similar across different measures, indicating that my results are robust across different measures. Overall, my research suggests that MiFID II is a successful regulation that significantly improved the information quality in European stock market.

1.3. Role of seniority in analyst teams: Evidence from China

Traditional implicit assumption is that sell-side reports and their EPS estimates are in general issued by individual analysts. Contrary to this implicit assumption, Fang and Hope (2021) find that more than 70% of sell-side reports in U.S. financial market are instead issued by analyst teams. Whether the performance of analyst teams is better than individual analysts is somewhat ambiguous across literature. What different characteristics of analysts that work in teams could predict such performances is also less explored in previous literature, especially the team structures, analysts status, and seniority of individual analysts within analyst teams. Groysberg, Polzer, and Elfenbein (2011) suggest that team performance benefits from star analysts within analyst teams to some extent, but this marginal benefit tend to vanish and even reverse if too many high-status analysts work together. Fang and Hope (2021) suggest that many characteristics are positively associated with higher accuracy of forecast estimates, including size of analyst teams, team members' abilities, and the level of diversities within teams. He, Jackson, and Li (2020) explore Chinese sell-side industry and suggest that analyst teams with clear hierarchy tend to perform better when comparing to flatter teams. They find that such teams tend to issue more accurate estimates with stronger market impact. Ewens and Rhodes-Kropf (2015) study the performance and investment skills of Venture Capital partners, providing an alternative and somewhat more direct way to observe the performance of team members within financial organizations.

In this paper, I test the role that senior analysts play within analyst teams and examine how seniority of individual analysts affect the overall performance of analyst teams. CSMAR provides the full names and the uniquely assigned analyst codes of all analysts that signed their names on each sell-side report published, thus providing a unique opportunity to study the relationship between characteristics of analyst teams and their overall performances. This is one of the most important reasons that I choose to focus on Chinese market when studying sell-side analysts in this research.

In this research, I find evidence to show that analysts tend to perform better when work in teams. I also study the role that seniority of analysts plays in determining the forecast performance and market impact separately for analyst teams and individual analysts. By double sorting on recommendation revision directions and seniority rankings, I show that analyst teams with higher mean seniority significantly outperform those with lower mean seniority, with higher market impact and lower forecast error. But I don't observe similar phenomenon for individual analysts that work by themselves. These combined results suggest that seniority plays important roles in determining the overall performance of analyst teams. It seems seniority of analysts is an important and valuable attribute only when analysts work together.

In some additional analyses, I further enhance the findings of my main results by using team-change as an opportunity to directly study the role of senior analysts within analyst teams. By exploring the relationship between seniority and PMAFE (a relative forecast performance measure) in team-change subsample, I find evidence to show that senior analysts significantly improve the relative forecast accuracy of an existing analyst team.

In summary, this study shows that seniority of sell-side analysts is an important determining factor of analyst teams' overall performance. However, it matters less when these analysts work alone by themselves.

1.4. Synchronicity and price informativeness: Evidence from analysts' recommendation revisions

Roll (1988) was among the first to study the role of synchronicity between individual stock returns and market returns in comprehending the price informativeness in the stock market. Synchronicity measures the relative amount of firm-specific information incorporated into stock prices; thus, lower synchronicity indicates higher amount of firm-specific information incorporated into stock prices and better price informativeness. Research based on similar assumptions includes Morck, Yeung, and Yu (2000), Piotroski and Roulstone (2004), Durnev, Morck, and Yeung (2005), Chan and Hameed (2006), Gul, Kim, and Qiu (2010), Crawford, Roulstone, and So (2012) and many others. Based on this assumption, lower synchronicity is considered as good attribute of a firm, indicating better information environment and stock price informativeness. However, this might not be the only way to interpret the role of synchronicity. Some other literature suggests that lower synchronicity actually indicates lower level of firm-specific information, therefore suggests worse information environment. For instance, Dasgupta, Gan, and Gao (2010) find that more transparent environment leads to higher return synchronicity, whereas Chan and Chan (2014) show synchronicity is positively associated with information environment by studying the seasoned equity offering discounts. Devos, Hao, Prevost, and Wongchoti (2015) suggest that lower synchronicity is associated with noisier and less informative information environment by studying the abnormal trading volume and volatility associated with recommendation revisions issued by sell-side analysts.

In this research, I try to explore the relationship between synchronicity and the level of firm-specific information incorporated into stock prices using recommendation revisions issued by sell-side analysts between 2010 and 2020 in Chinese market. I find evidence to show that lower synchronicity indicates higher amount of firm-specific information incorporated into stock prices, thus indicating better price informativeness. I study the change of synchronicity around recommendation revisions issued by sell-side analysts, which are usually associated with distribution of new firm-specific information about the target firm. Synchronicity of these target underlying firms significantly decreases after recommendation revisions, suggesting a negative relationship between amount of firm-specific information incorporated into stock prices and synchronicity. By plotting the R-squared values on a daily basis before and after recommendation revision announcement days, I find that the decrease in synchronicity on average starts around 15 trading days ahead of the actual public announcements of recommendation revisions. This evidence suggests the potential leak of valuable firm-specific information from sell-side analysts way before the actual announcement days.

My research also shows that recommendation revisions issued by senior analysts (teams) and those recommendation revisions issued on target firms with lower analyst coverage contain more firm-specific information when holding everything else equal. I also find evidence to show that influential revisions with statistically significant market impact tend to contain more firm-specific information within upgrade subsample, whereas influential revisions contain less firm-specific information within downgrade subsample.

Chapter 2. Analyst incentives and stock return synchronicity: Evidence from MiFID II

2.1. Introduction commentary

This chapter explores how MiFID II changes the overall price informativeness of European stock market through changing the incentives of sell-side analysts. Since this chapter is already published as an academic paper in Financial Analysts Journal, I've attached the CC BY OPEN ACCESS LICENSE and the full paper as published in section 2.2 and section 2.3 according to the latest requirements of University of Bath. In section 2.4, I show the Internet Appendix of this published paper, which contains many alternative analyses that complement the main results. In section 2.5, I conclude the main findings of this paper and introduce next two chapters.

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2.3. Analyst incentives and stock return synchronicity: Evidence from MiFID II (as published in Financial Analysts Journal)

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Research

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Analyst Incentives and Stock Return Synchronicity: Evidence from MiFID II

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Yihan Li is a PhD candidate in the School of Management, University of Bath. Xin Liu is an assistant professor in the School of Finance, Renmin University of China. Vesa Pursiainen is an assistant professor in the School of Finance, University of St. Gallen, and at the Swiss Finance Institute. Send correspondence to Xin Liu at xinl@ruc.edu.cn.

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

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

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

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

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

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

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

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

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

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

If the impact of MiFID II is driven by a change in analyst incentives, we might expect it to have a larger effect on firms that are more important to the analysts covering them and the brokers employing the analysts.[11] To test this prediction, we construct several proxies for the relative importance of firms to the analysts covering them. Similar to Harford et al. (2019), we use within-analyst market capitalization, trading volume, and institutional ownership rankings to measure the importance of a firm to an analyst. We also look at the quality of the analysts covering the firms, based on the average precision of their earnings estimates relative to other analysts covering the same firms. Across all these measures of firm importance to the analyst or broker, more important firms experience significantly larger reductions in return synchronicity. Another indication of increased competitive pressure for analysts covering a given firm is the reduction in analyst coverage of that firm amid MiFID II. Hence, we perform an analysis conditional on the change in the number of analysts covering the firm. We find that firms experiencing a reduction in analyst coverage are also the ones where stock return synchronicity decreases the most, suggesting that the incentive effects of the regulatory change are largest in these stocks.

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

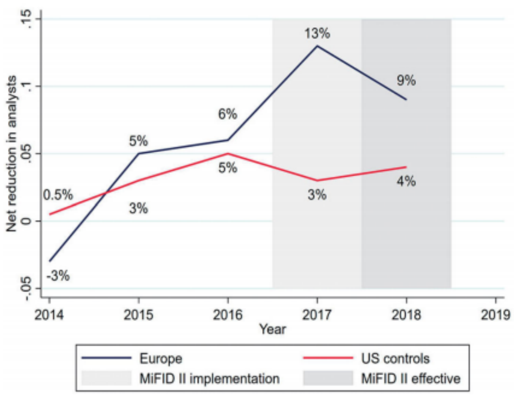
A possibly important implication of MiFID II is the directionality of changes in stock return synchronicity. There are several reasons why the information provided by analysts might be more important for negative than for positive returns.[12] First, management is likely to be incentivized to make sure positive news is accurately reflected in the share price, while the same is not necessarily the case for negative news. Hence, analyst-generated information may be particularly important for negative returns. Second, there are general differences in market correlations depending on market conditions, and a relative decrease in synchronicity might cause a larger absolute effect in negative correlations.[13] Finally, information production itself may be asymmetric and depend on the market direction.[14] Motivated by these insights, we study the effect of MiFID II on stock return synchronicity separately during days of negative and positive market returns. We find stock return synchronicity decreases significantly more during negative days than during positive days. This suggests that stock prices incorporate more negative firm-specific information and become less contagious to negative shocks, reducing the systematic negative risk component in stock returns.[15]

Our study makes several contributions. First, we provide novel insights on the impacts of unbundling equity research (e.g., Bender et al. 2021) and the effects of MiFID II specifically. Earlier literature on unbundling focuses mostly on the effects on fund investors and conflicts of interest for brokers, not on analyst incentives. In contrast, prior studies of MiFID II focus largely on the effect on individual analyst incentives and outputs, with very little (and somewhat mixed) evidence of firm- and market-level effects.[16] We show that the net effect of the previously documented analyst- and firm-level changes are that aggregate stock price informativeness significantly improves.[17] This finding is significant for investors, possibly favoring passive investors and disadvantaging active ones. It also has important implications for firms, as more informative stock prices are likely to improve investment efficiency (e.g., Chen, Goldstein, and Jiang 2007).

Our findings on the asymmetric effect of MiFID II on return synchronicity are novel in both the stock return synchronicity literature as well as the literature on MiFID II specifically. We show that the information environment can have a differential effect on negative and positive return synchronicity.[18] This implies that stock prices become less contagious to negative shocks and reduce the negative systematic risk component in stock returns. The decrease in negative return correlations is likely a positive thing for (long) investors with concentrated portfolios, as it limits their exposure to systematic downside risk.

More broadly, a large literature focuses on the information content of analyst estimates and stock recommendations.[19] We contribute to this literature by showing that the institutional environment can have important consequences on the information that analysts produce. Our study is also related to the literature on the determinants of stock price

Figure 1. Reduction in the Total Number of Analysts



This figure shows the net reduction in total number of analysts as a percentage in both the European market and US market each year. Analysts leave the market if they stop providing earnings estimates in I/B/E/S. The numbers are computed based on the number of unique equity analysts in the I/B/E/S universe in each year.

informativeness and comovement. These include voluntary information disclosure by firms (Haggard, Martin, and Pereira 2008), the enforcement of insider trading laws (Fernandes and Ferreira 2009), news about fundamentals (Albuquerque and Vega 2009) and investor attention (Huang et al. 2019). We show that regulatory reforms can have significant implications on market-wide stock return synchronicity.

Our findings are also highly policy-relevant for assessing the successfulness of the MiFID II framework adopted by the EEA. Our results suggest that this reform not only achieved stronger incentives and hence more individual effort by analysts, but also improved the overall information environment while reducing the number of analysts producing the information. In a sense, MiFID II seems to have generated more from less, which might be viewed as an encouraging sign of its overall impact.

Data and Methodology

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

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

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

Table 1. Summary Statistics

A. European firms and matched control firms

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

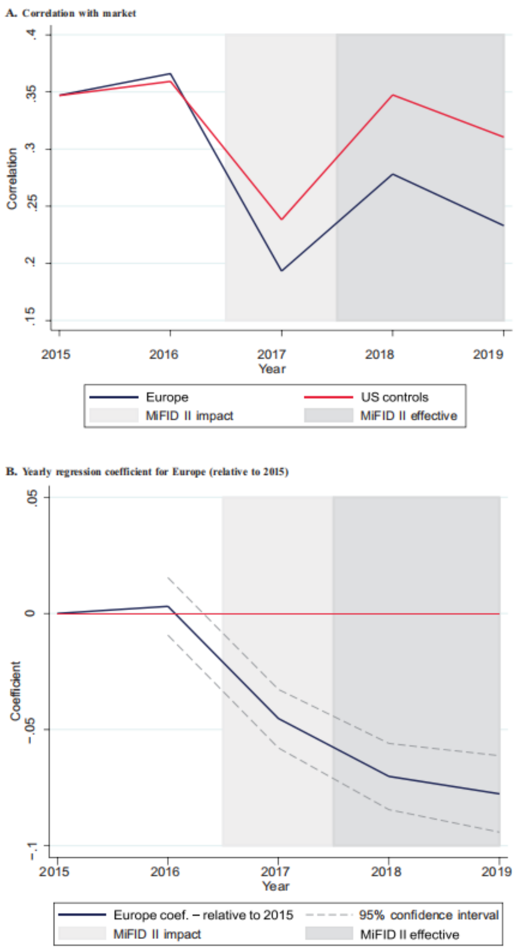
B. European firms vs. matched control firms

	Europe		Control (US)		Control – Europe
	Mean	Std.	Mean	Std.	Δ Mean
Synchronicity					
Correlation	0.285	0.198	0.320	0.183	0.035***
Corr.(Positive)	0.175	0.166	0.216	0.156	0.041***
Corr.(Negative)	0.255	0.182	0.263	0.171	0.008****
Corr.(Difference)	0.081	0.138	0.047	0.132	−0.033***
R-sqr (index)	0.120	0.139	0.136	0.127	0.015***
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

Panel A shows the summary statistics for the firm-year observations in the sample. *Correlation* is the yearly correlation coefficient between daily stock returns and daily market returns. *Corr.(Positive)* is calculated as the correlation coefficient between daily stock returns and the market index returns from the trading days when the market index return is positive. *Corr.(Negative)* is calculated as the correlation coefficient between daily stock returns and the market index returns from the trading days when the market index return is negative. *Corr.(Difference)* is calculated as *Corr.(Negative)* minus *Corr.(Positive)*. *Analyst coverage* is the average number of analysts covering the firm. *RoE* is return on equity, computed as net income divided by the book value of equity. *Turnover rate* is calculated as the yearly trading volume divided by the number of shares outstanding. *Past return* is the stock return from the past year. *Volatility* is the standard deviation of daily stock returns over each year. Panel B shows a comparison of European firms and US control firms. ** and *** indicate significance at the 5% and 1% levels, respectively.

Stock Return Synchronicity and Asymmetry. We use STOXX 600 as the European market index and S&P 500 as the US market index. For each calendar year, we compute stock return synchronicity for each European (US) firm as the pairwise correlation in currency-adjusted daily returns between the firm and STOXX 600 (S&P 500). In later sections of this paper, we also consider alternative proxies to capture price informativeness from different perspectives.

Figure 2. Return Synchronicity of European Firms vs. US Controls



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

$$Correlation_{i,t} = \alpha_i + \gamma_{s(i),t} + \beta \times Europe_i \times Year + \varphi \times X_{i,t} + \varepsilon_{i,t},$$

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 US 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.

Similar to Bris et al. (2007), we further explore the asymmetry in stock return synchronicity during positive and negative market returns. We divide all trading days in a calendar year into two groups: positive and negative market return days. We calculate the pairwise correlation of daily returns between a firm and the market index during negative days (*Corr.(Negative)*) and positive days (*Corr.(Positive)*). We construct *Corr.(Difference)*, calculated as *Corr.(Negative)* less *Corr.(Positive)*, to capture the asymmetry in stock return synchronicity. This methodology is similar to Huang et al. (2020) and consistent with the analysis of Ang et al. (2006).

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

Main Results

MiFID II and Stock Return Synchronicity.

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

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

$$\begin{aligned} Correlation_{i,t} &= \alpha + \beta \times Europe_i \times Post_t \\ &+ \gamma \times Europe_i + \theta \times Post_t + \varphi \times X_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{1}$$

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

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

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

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

We perform the following regression analyses:

$$\begin{aligned} Correlation_{i,t} = \alpha &+ \beta_1 \times Europe_i \times Post_t \times High\ imp._i \\ &+ \beta_2 \times Post_t \times High\ imp._i \\ &+ \beta_3 \times Europe_i \times Post_t + \varphi \times X_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

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

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

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

To test this prediction and to show the cross-sectional variation of our main results conditional on changes in analyst coverage, we re-examine our baseline regressions by including triple interaction terms with respect to changes in analyst coverage. More specifically, we define *I(Drop)* as a dummy variable that equals one if a firm experiences analyst drops after the adoption of MiFID II, and zero otherwise. We further divide *I(Drop)* into two variables based on the median drop value, and *I(Drop = High)* (*I(Drop = Low)*) is a dummy variable that equals one if a firm experiences above-median (below-median) analyst drops after the adoption of MiFID II, and

Table 2. Stock Return Synchronicity and MiFID II

	(1)	(2)	(3)	(4)	(5)
Europe × Post	−0.067***	−0.064***	−0.064***	−0.063***	−0.064***
	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
Europe	0.004	0.017**	0.017**	-	-
	(0.008)	(0.007)	(0.007)	-	-
Post	−0.058***	−0.066***	-	−0.070***	-
	(0.006)	(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	25,080	25,053	25,053
R^2	0.071	0.552	0.607	0.807	0.832

The dependent variable is *Correlation*, the yearly correlation coefficient between daily stock returns and daily market returns. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

zero otherwise. Similarly, *I(No Change)* is a dummy variable that equals one for firms without changes in analyst coverage. Results are reported in Table 4.

Table 4 confirms our conjecture. In column (1), the coefficient for *Europe* × *Post* × *I(Drop)* is significantly negative. This indicates that, for firms with analyst drops after the adoption of MiFID II, their return synchronicity drops 2.7% more than the rest of the firms. This effect is not only statistically significant, but also economically meaningful, considering the effect for the rest of the firms (the coefficient for *Europe* × *Post*) is −5.3%. After we further decompose *I(Drop)* into *I(Drop* = *High)* and *I(Drop* = *Low)*, column (2) shows that our main results mainly come from firms with more analyst drops. For firms with more analyst drops after the adoption of MiFID II, their return synchronicity drops 3.9% more than the rest of the firms. For firms with less analyst drops after the adoption of MiFID II, their return synchronicity drops only 0.7% more than the rest of the firms, which is not statistically significant. Moreover, column (3) shows that the coefficient for *Europe* × *Post* × *I(No Change)* is positive and significant. This indicates that our main result becomes weaker for the subsample of firms without changes in analyst coverage. In column (4), similar results are obtained if we include all the triple interaction terms in the same regression.

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

MiFID II and Forecast Accuracy. As MiFID II incentivizes analysts to increase effort, it might be expected to induce equity analysts to provide more accurate information. We test this by examining analysts' earnings forecasts. If MiFID II indeed significantly changes analysts' incentives to produce better

Table 3. MiFID II Impact and Analyst Incentives

	(1)	(2)	(3)	(4)	(5)
Europe × Post × High mcap	−0.018**	–	–	–	–
	(0.008)	–	–	–	–
Post × High mcap	−0.012	–	–	–	–
	(0.006)	–	–	–	–
Europe × Post × High prop. mcap	–	−0.021***	–	–	–
	–	(0.007)	–	–	–
Post × High prop. mcap	–	0.002	–	–	–
	–	(0.003)	–	–	–
Europe × Post × High trading volume	–	–	−0.025***	–	–
	–	–	(0.008)	–	–
Post × High trading volume	–	–	−0.010	–	–
	–	–	(0.006)	–	–
Europe × Post × High inst. ownership	–	–	–	−0.027**	–
	–	–	–	(0.010)	–
Post × High inst. ownership	–	–	–	−0.010	–
	–	–	–	(0.008)	–
Europe × Post × High accuracy	–	–	–	–	−0.014**
	–	–	–	–	(0.005)
Post × High accuracy	–	–	–	–	−0.002
	–	–	–	–	(0.005)
Europe × Post	−0.051***	−0.050***	−0.048***	−0.048***	−0.054***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
N	22,295	22,295	22,309	20,398	23,475
R^2	0.833	0.833	0.833	0.832	0.833

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

estimates, we should expect to see their consensus estimates becoming more accurate. This could serve as an important implication to investors in response to the adoption of MiFID II.

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

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

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

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

Table 4. Stock Return Synchronicity and Change in Analyst Coverage

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

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

absolute forecast error decreases after the adoption of MiFID II, and zero otherwise. To explore more cross-sectional variation, we further decompose *I(Drop)* into two groups based on the median of forecast improvement. *I(Drop = High)* (*I(Drop = Low)*) is a dummy variable that equals one if the firm experiences above-median (below-median) improvement in forecast accuracy, and zero otherwise. Results are reported in Table 6.

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

The improvement in forecast accuracy should also have an impact on price reactions to unexpected earnings news. Given the improvements in analysts' forecast accuracy, European stock prices should react more strongly in response to unexpected earnings news. This price sensitivity can be captured by

Table 5. Forecast Accuracy and MiFID II

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

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

regressing the cumulative abnormal return from the earnings announcement to standardized unexpected earnings. Here, we use the cumulative abnormal return from the [−1, 1] window to capture the price reactions to earnings news, where $t = 0$ is the earnings announcement day (or the ensuing trading day if the news is announcement in a non-trading day or after markets close). Abnormal returns are computed as the Fama-French three-factor adjusted returns using betas computed from the previous year. Standardized unexpected earnings (*SUE*) is computed as the difference between the actual EPS announcement and analysts' EPS forecast consensus, divided by share price. We consider a triple interaction term, *SUE* × *Europe* × *Post*, to capture the incremental price sensitivity for European firms after the adoption of MiFID II. Results from Table 7 shows that, after the adoption of MiFID II, European firms' stock prices become more sensitive to unexpected earnings surprises, compared to their U.S. counterparts.

Additional Results

Positive versus Negative Return Synchronicity. The findings of Bris et al. (2007) suggest that a change in the aggregate information environment might be expected to have asymmetric effects on stock return synchronicity, depending on the direction of the market. Their results suggest that short selling may reduce the negative-minus-positive return synchronicity difference, implying that more firm-specific negative information is incorporated. This might be true also of analyst-provided information. Firm management is likely to be incentivized to make sure positive news are accurately reflected in the share price, while the same is not necessarily the case for negative news. Hence, analyst-generated information may be particularly important for negative returns. This would imply that the difference between negative and positive return synchronicity decreases if analysts produce better-quality information.

Table 6. Stock Return Synchronicity and Change in Forecast Accuracy

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

The dependent variable is *Correlation*, the yearly correlation coefficient between daily stock returns and daily market returns. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. For each firm, the absolute forecast error is calculated as the absolute difference between analysts' EPS forecast consensus and the actual EPS, divided by share price. *I(Drop)* is a dummy variable that equals one if a firm's absolute analyst forecast error decreases after MiFID II. We further divided this subsample into two groups based on its median decrease. *I(Drop = High)* is a dummy variable that equals one for firms with above-median forecast improvement, while *I(Drop = Low)* is a dummy variable that equals one for firms with below-median forecast improvement. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

Another reason that this might happen is that there are general differences in market correlations depending on market conditions, as observed by Ang et al. (2006) and Huang et al. (2020), and a relative decrease in synchronicity might cause a larger absolute effect in negative return correlations. Finally, information production itself may be asymmetric and depend on the market direction. This idea parallels the findings of Veldkamp (2005), who argues that more information is generated at times of economic expansion than in periods of contraction, and that this leads to gradual booms and sudden crashes in asset prices. Brockman et al. (2010) provide empirical support for these predictions, showing that stock comovement is countercyclical, and that the relationship between business cycle and comovement is stronger in countries with less developed financial markets and less transparent information. This might also imply that analyst-generated information is more important in negative returns.

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

The results are shown in Table 8. While stock price informativeness improves significantly (decrease in

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

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

The dependent variable is *CAR*[−1, 1], the cumulative abnormal return from the [−1, 1] window, where $t = 0$ is the earnings announcement day (or the ensuing trading day if the news is announcement in a non-trading day or after markets close). Standard unexpected earnings (*SUE*) is defined as the difference between the actual EPS announced and the EPS forecast consensus, divided by share price. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

market correlation) for both positive and negative market return days, the effect is more than twice as large during negative days. Columns 5–6 show that this difference is also statistically significant. For example, after controlling for firm and industry-year fixed effects, the market correlation for European firms falls by 5.4% points more during negative days than during positive days after the introduction of MiFID II. This suggests that stock prices incorporate relatively more firm-specific information during days of negative returns. It also implies stock prices being less contagious to negative shocks and reducing the systematic negative risk component in stock returns.

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

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

Table 8. Positive versus Negative Return Synchronicity

	Corr.(Positive)		Corr.(Negative)		Corr.(Difference)	
	(1)	(2)	(3)	(4)	(5)	(6)
Europe × Post	−0.046***	−0.046***	−0.101***	−0.102***	−0.056***	−0.056***
	(0.006)	(0.006)	(0.008)	(0.009)	(0.007)	(0.007)
Europe	−0.006	–	0.061***	–	0.067***	–
	(0.004)	–	(0.009)	–	(0.006)	–
Post	−0.042***	–	−0.046***	–	−0.004	–
	(0.006)	–	(0.006)	–	(0.007)	–
Ln(Market value)	0.085***	0.049***	0.075***	0.064***	−0.010***	0.016**
	(0.007)	(0.008)	(0.009)	(0.009)	(0.002)	(0.007)
B/M	0.004	0.008**	0.002	0.002	−0.002	−0.006
	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.003)
RoE	0.001	0.000	0.002	0.001	0.000	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Volatility	−0.012***	−0.003	−0.019***	0.002	−0.007	0.005
	(0.003)	(0.002)	(0.006)	(0.003)	(0.004)	(0.003)
Past return	0.002	0.006***	0.005***	0.002	0.002	−0.004***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Turnover rate	0.003	0.005	0.009**	0.006	0.006	0.002
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)
Ln(1 + Analyst coverage)	0.016***	0.008	0.017***	0.010**	0.001	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	25,072	25,045	25,072	25,045	25,072	25,045
R^2	0.464	0.711	0.408	0.699	0.043	0.301

The dependent variable is shown above each column. *Corr.(Positive)* is calculated as the correlation coefficient between daily stock returns and the market index returns from the trading days when the market return is positive. *Corr.(Negative)* is calculated as the correlation coefficient between daily stock returns and the market index returns from the trading days when the market return is negative. *Corr.(Difference)* is calculated as *Corr.(Negative)* minus *Corr.(Positive)*. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015–2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively.

unpredictable, and stock returns should have zero autocorrelation. Therefore, a reduction in autocorrelation can suggest improvement in market efficiency. Column 1 in Table 9 shows that the coefficients for *Europe* × *Post* is significantly negative, suggesting that market efficiency is improved for European firms following the introduction of MiFID II.

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

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

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} = \alpha_i + \frac{\sigma_{im}}{\sigma_m^2} R_{m,t} + \varepsilon_{i,t}, \quad (3)$$

where $\sigma_{im} = COV(r_{i,t}, R_{m,t})$ and $\sigma_m^2 = VAR(R_{m,t})$. Firm-specific return variation is estimated for each firm-year as

$$\sigma_{i\varepsilon}^2 = \sigma_i^2 - \frac{\sigma_{im}^2}{\sigma_m^2}. \quad (4)$$

From the absolute firm-specific return variation, $\sigma_{i\varepsilon}^2$, we compute the relative firm-specific return variation:

$$\Psi_i = \log\left(\frac{\sigma_{i\varepsilon}^2}{\sigma_i^2 - \sigma_{i\varepsilon}^2}\right). \quad (5)$$

Column 2 in Table 9 shows that firm-specific return variation significantly increases for European firms after the adoption of MiFID II.

Table 9. Alternative Measures of Price Informativeness

	(1) Return Autocorrelation	(2) Firm-Specific Return Variation	(3) Return Autocorrelation Conditional on Trading Volume	(4) *R*-Sqr.(Index)
Europe × Post	−0.013**	0.714***	0.037***	−0.040***
	(0.005)	(0.077)	(0.009)	(0.004)
Ln(Market value)	0.011	−1.018***	−0.005	0.040***
	(0.008)	(0.129)	(0.009)	(0.006)
B/M	0.004	−0.038	−0.001	0.001
	(0.004)	(0.050)	(0.005)	(0.002)
RoE	0.000	0.009	0.002	−0.002
	(0.002)	(0.015)	(0.002)	(0.001)
Volatility	−0.009**	0.000	−0.003	−0.002
	(0.004)	(0.035)	(0.005)	(0.002)
Past return	−0.002**	−0.048	0.003	0.003***
	(0.001)	(0.028)	(0.003)	(0.001)
Turnover rate	0.007***	−0.109***	0.004	0.002
	(0.002)	(0.032)	(0.003)	(0.002)
Ln(1 + Analyst	0.008	−0.187***	0.000	0.004
coverage)	(0.004)	(0.039)	(0.005)	(0.003)
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
N	25,047	25,047	25,043	25,053
R^2	0.471	0.723	0.313	0.806

In column (1), the dependent variable is the daily return autocorrelation in each year. In column (2), the dependent variable is the firm-specific return variation. In column (3), the dependent variable is the daily return autocorrelation conditional on trading volume. In column (4), *R-sqr.(index)* is the *R*-squared from a regression of daily stock return on daily 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. ** and *** indicate significance at the 5% and 1% levels, respectively.

The third measure we consider is return autocorrelation conditional on trading volume (e.g., Llorente et al. 2002). To construct this for each firm-year, we estimate the following time-series regression using daily returns:

$$r_{i,t} = \alpha_i + \beta_i r_{i,t-1} + \gamma_i r_{i,t-1} V_{i,t-1} + \varepsilon_{i,t}. \quad (6)$$

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

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

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

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

Robustness Checks and Additional Analyses.

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

Robustness Checks.

1. ***Firms with no MTF trading***. MiFID II entails components that are not related to analysts. In particular, the limitations of dark pool trading volumes might affect some of our findings. To test this, we repeat our main analysis for a subsample of European firms that do not have any MTF trading in our sample period.[24] Given MTFs include dark pools, this subsample should not be substantially affected by new rules concerning dark pools. As shown in Appendix Table A2, our findings remain similar when including only firms with no MTF trading.
2. ***Excluding Switzerland***. In our main sample, we include firms located in Switzerland in the analysis, even though it is not a part of EEA and hence not directly affected by the legislation. Given its capital market is closely integrated with those of the EEA and a large part of the analyst coverage of Swiss firms takes place within the EEA, it seems likely that Switzerland is equally affected by the changes. In Appendix Table A3, we repeat the analysis excluding Switzerland and obtain similar results, confirming that our findings are not substantially affected by the inclusion of Switzerland.
3. ***Alternative sample constructions***. To make sure our findings are not driven by the methodology we use to construct the matched control sample, we perform three robustness check analyses. In Appendix Table A4, instead of using only matched US control firms, we include all US firms into the sample without any matching or limitations, i.e. a control group without any matching. We also construct a second matched control group, using more granular propensity score matching process within each 2-digit NAICS industry and include firm size, book-to-market ratio, past return, return on equity, turnover rate, and volatility (i.e., all firm-level control variables we include in the regressions) as the independent variables. This analysis is reported in Appendix Table A5. Finally, we also extend our sample to include observations from 2014 and reexamine our baseline results in Appendix Table A6. With all of these alternative samples, the results remain similar to our main results from Table 2.
4. ***Alternative treatment timing***. In our analysis, we define the years from 2017 onwards as post-MiFID II. Formally, the directive came into force in January 2018, but the details of the directive had been finalized in early 2017, and the changes in the structure of the analyst industry take place mostly already in 2017 when the largest reduction in the number of analysts occurs. In Appendix Table A7, we show that our main results remain qualitatively similar when defining the post-MiFID II period as the beginning of 2018 instead.
5. ***Alternative frequencies of observations***. In our main analysis, we compute return synchronicity at an annual frequency. To make sure our findings are robust across different estimation windows, in Appendix Table A8, we construct return synchronicity based on monthly and quarterly frequencies. We repeat the analysis using these two alternative synchronicity proxies and obtain similar results.

Additional Results.

1. ***Placebo test.*** To confirm that our results are driven by the change in analyst incentives, instead of other components of MiFID II, we conduct a placebo test using European firms that have never been covered by any analyst during our sample period. If the general decrease in synchronicity is driven by analysts producing better-quality information, we should not observe a reduction in synchronicity for these firms. Appendix Table A9 shows that there exists no significant change in return synchronicity for this set of European firms after the adoption of MiFID II, confirming our main analysis from an alternative perspective.
2. ***Stock price crash risk***. We document that the introduction of MiFID II is associated with a significant decrease in stock return synchronicity, and the effect is significantly larger for negative returns. This can be interpreted as a reduction in exposure to systematic negative risk. Hence, we also explore an idiosyncratic component of negative risk, stock price crash risk. In Appendix Table A10, we find that MiFID II is associated with a significant reduction in stock price crash risk.

3. ***MiFID II and variance ratio***. To examine whether MiFID II improves market efficiency, we follow Boehmer and Kelley (2009) and Chen, Kelly, and Wu (2020) to construct variance ratio. Because both positive and negative deviations of variance ratio form one represent stock price movement departing from a random walk, we use $|1-VR(n,m)|$ as a measure of market efficiency, where *VR(n,m)* is the ratio of the return variance over *m* days to the return variance over *n* days, both divided by the number of the days. If prices follow a random walk, the deviation should be zero. Larger magnitude of this deviation reveals weaker market efficiency. Appendix Table A11 shows that MiFID II is associated with improved market efficiency, though the results are not always statistically robust.
4. ***MiFID II and price delay.*** To test whether MiFID II also affects the speed of stock prices incorporating market-wide information, we construct three different measures of price delay suggested by Hou and Moskowitz (2005) and used by, e.g., Bris et al. (2007) and Busch and Obernberger (2017). These measures all consider market return as a proxy for new information and quantify how average prices adjust to it. Therefore, it is worth noting that these measures do not capture the price reaction to firm-specific information. In Table A12, we find that MiFID II is associated with an increase in price delay. This suggests that the adoption of MiFID II makes stock prices more informative to firm-specific information due to higher quality information production from equity analysts but reduces the speed of price reaction to market-wide information.
5. ***MiFID II and future earnings return coefficient***. The future earnings return coefficient (e.g., Durnev et al. 2003) can also capture price informativeness. This is a sum of coefficients obtained from cross-sectional regressions in each year for different groups of firms. In other words, it is no long a firm-level proxy. Even though this proxy is not ideal for our research agenda, we still construct future earnings return coefficient at each 2-digit NAICS industry level and examine whether price informativeness improves for European industries after the adoption of MiFID II. Internet Appendix Table A13 indicates potential increase in future earnings return coefficient for European industries after the adoption of MiFID II, though the results are not statistically significant.
6. ***Stock return synchronicity by year***. To confirm that our analysis is not simply capturing ongoing trends unrelated to MiFID II, we perform an analysis of stock return synchronicity, as well as the down-up difference in synchronicity, by year. We include all the interactions between Europe and the year dummies in our main regression and report the results in Internet Appendix Table A14. There is no significant difference between 2016 and 2015 in any of the regression specifications. In 2017, the market correlation decreases by approximately 4.5% points for European firms, relative to the matched US peer firms, and in 2018 this decrease relative to 2015 grows further to 7.0% points, and slightly further to 7.8% points in 2019. This suggests that in 2017, the year leading up to the formal MiFID II implementation, slightly more than half of the full MiFID II effect takes place, and the remainder happens in 2018 and 2019. A similar pattern can be seen for the down-up difference in correlation. The timing of the effect is notable as it helps as confirm that at least part of the effects we measure are directly attributable to changes in analyst incentives, as none of the other MiFID II rules related to trade reporting and dark pools could have plausibly affected the market in 2017.
7. ***Alternative correlation and R-squared specifications***. In our analyses, we measure stock return synchronicity using the annual correlation between daily stock returns and daily returns of the aggregate market index. Given there are alternative measures of synchronicity used in prior literature, in this section, we consider six different alternative measures to make sure that our results are not driven by the choice of synchronicity measure. The alternative measures of synchronicity include stock return correlation with a value-weighted market return index of its headquarter country, *R*-squared from regressions of daily stock return on aggregate market index, value-weighted market index return of its headquarter country, and value-weighted industry index return. Results reported in Internet Appendix Table A15 are very similar to our main results reported in Table 2.
8. ***Controlling for institutional ownership***. One potential driver of stock return synchronicity could be the amount of passive investments (e.g., Anton and Polk 2014). Therefore, in Internet

Appendix Table A16, we control for total institutional ownership in our baseline regressions. Even though high institutional ownership indeed generates strong return synchronicity, our baseline result on the reduction of return synchronicity for European firms after the adoption of MiFID II remains qualitatively similar.

Discussion and Conclusion

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

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

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

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

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

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

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

Editor's Note

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Notes

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

21. For robustness, we also consider other matching schemes. See Section 4.3 for more details.

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

23. We thank an anonymous referee for this suggestion.

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

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2.4. Analyst Incentives and Stock Return Synchronicity: Evidence from MiFID II

Internet appendix

A1. Additional summary statistics

In this section, we present additional summary statistics of our main sample by country and year.

Table A1: Summary statistics by country and year

Panel A shows the number of firms in each country in Europe. The sample includes 2817 European firms in 30 European countries in total. Panel B shows the number of European firms in the sample each year.

Panel A: By country	
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
Luxembourg	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
Total	2817

Panel B: By year

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

A2. Robustness checks

A2.1 Firms with no MTF trading

MiFID II entails components that are not related to analysts. In particular, its limitations of dark pool trading volumes 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 or MTF trade transparency requirements.

The results, shown in Table A2, 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.

Table A2: 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 US 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(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
R2	0.429	0.490	0.761	0.788

A2.2 Excluding Switzerland

In our main sample, we include firms located in Switzerland in the analysis, even though it is not a part of EEA and hence not directly affected by the legislation. Given its capital 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. In Table A3, we repeat the analysis excluding Switzerland and obtain similar results, confirming that our findings are not substantially affected by the inclusion of Switzerland.

Table A3: Stock return synchronicity and MiFID II: excluding Switzerland

Firms in Switzerland are excluded in this test. The dependent variable is *Correlation*, the yearly correlation coefficient between daily stock returns and daily market returns. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015-2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Europe × Post	-0.067***	-0.068***	-0.067***	-0.069***
	(0.006)	(0.006)	(0.007)	(0.007)
Europe	0.021***	0.021***		
	(0.007)	(0.006)		
Post	-0.067***		-0.070***	
	(0.005)		(0.005)	
Ln(Market value)	0.104***	0.107***	0.093***	0.078***
	(0.009)	(0.007)	(0.012)	(0.008)
B/M	0.003	0.005***	0.007*	0.004
	(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	-0.019***	-0.011***	-0.008**	0.003
	(0.005)	(0.002)	(0.003)	(0.002)
Past return	0.005***	0.004**	0.005***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
Turnover rate	0.010**	0.006**	0.012***	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.021***	0.024***	0.007*	0.013***
	(0.004)	(0.003)	(0.004)	(0.004)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	23,730	23,730	23,703	23,703
R2	0.555	0.608	0.808	0.832

A2.3 Non-matched sample

To make sure our findings are not driven by the methodology we use to construct the matched control sample, in Table A4, instead of using only matched US control firms, we include all US firms into the sample without any matching or limitations, i.e. a control group without any matching. Results from Appendix Table A4 are similar to what we report in Table 2.

Table A4: 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 US 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. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Europe × 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

A2.4 Alternative control group matching

In our baseline specification, 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, we consider firm size, book-to-market ratio, and past return as the independent variables. We first select the U.S. firms with close propensity scores and then minimize the difference in analyst coverage to obtain the closest match for each European firm in our sample.

To make sure our results are not driven by the matching methodology, we conduct a similar but more granular propensity score matching process within each 2-digit NAICS industry and include firm size, book-to-market ratio, past return, return on equity, turnover rate, and volatility (i.e., all firm-level control variables we include in the regressions) as the independent variables. We re-examine our main result based on this alternative sample. Table A5 shows that our results remain qualitatively similar.

Table A5 Stock return synchronicity and MiFID II – alternative control group

The dependent variable is *Correlation*, the yearly correlation coefficient between daily stock returns and daily market returns. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015-2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Europe × Post	-0.072***	-0.074***	-0.073***	-0.076***
	(0.010)	(0.010)	(0.010)	(0.010)
Europe	0.042***	0.042***		
	(0.008)	(0.008)		
Post	-0.056***		-0.060***	
	(0.011)		(0.011)	
Ln(Market value)	0.107***	0.109***	0.119***	0.102***
	(0.008)	(0.008)	(0.017)	(0.014)
B/M	0.000	0.004*	0.011**	0.008*
	(0.003)	(0.002)	(0.004)	(0.004)
RoE	-0.002	-0.001	-0.002	0.000
	(0.003)	(0.002)	(0.002)	(0.002)
Volatility	-0.026***	-0.019***	-0.012**	0.001
	(0.006)	(0.005)	(0.005)	(0.005)
Past return	0.005**	0.004**	0.005*	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Turnover rate	0.028***	0.024***	0.023***	0.018***
	(0.002)	(0.003)	(0.003)	(0.003)
Ln(1+Analyst coverage)	0.018***	0.023***	0.003	0.011**
	(0.004)	(0.004)	(0.005)	(0.004)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	24,132	24,132	24,085	24,085
R2	0.579	0.636	0.812	0.839

A2.5 Extended sample period

We extend our sample to include observations from 2014 and re-examine our baseline results in Table A6. The results remain similar to our main results in Table 2.

Table A6: Stock return synchronicity and MiFID II – Including 2014

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 2014-2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Europe × Post	−0.043***	−0.043***	−0.044***	−0.046***
	(0.006)	(0.006)	(0.006)	(0.006)
Europe	−0.005	−0.006		
	(0.007)	(0.007)		
Post	−0.066***		−0.070***	
	(0.004)		(0.005)	
Ln(Market value)	0.105***	0.106***	0.102***	0.069***
	(0.009)	(0.007)	(0.010)	(0.007)
B/M	0.002	0.005***	0.006*	0.002
	(0.003)	(0.002)	(0.003)	(0.003)
RoE	0.002	0.003**	−0.002	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Volatility	−0.017***	−0.011***	−0.005*	0.002
	(0.005)	(0.002)	(0.003)	(0.003)
Past return	0.005***	0.006***	0.002	0.006***
	(0.001)	(0.002)	(0.001)	(0.001)
Turnover rate	0.008*	0.004	0.009***	0.005**
	(0.004)	(0.003)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.022***	0.026***	0.010***	0.017***
	(0.004)	(0.003)	(0.003)	(0.002)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	29,314	29,314	29,291	29,291
R2	0.550	0.606	0.797	0.825

A2.6 Alternative treatment timing

In our analysis, we define the years from 2017 onwards as post-MiFID II. Formally, the directive came into force in January 2018, but the details of the directive had been finalized in early 2017, and the changes in the structure of the analyst industry take place mostly already in 2017, when the largest reduction in the number of analysts occurs.

In this section, we repeat our main analysis but define post-MiFID II period as beginning from 2018 instead. As shown in Table A7, the results remain similar to our main results, confirming that the choice of treatment timing is not consequential to the findings.

Table A7: 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. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(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
R2	0.491	0.605	0.748	0.831

A2.7 Alternative frequencies of observations

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

Table A8: Stock return synchronicity and MiFID II – Different frequencies

In Panel A, the dependent variable is the monthly correlation coefficient between daily stock returns and daily market returns. In Panel B, the dependent variable is the quarterly correlation coefficient between daily stock returns and daily market returns. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015-2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	Panel A: Monthly frequency				Panel B: Quarterly Frequency			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Europe × Post	−0.016**	−0.016**	−0.017***	−0.018***	−0.035***	−0.035***	−0.036***	−0.036***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Europe	−0.029***	−0.030***			−0.009	−0.009		
	(0.007)	(0.007)			(0.007)	(0.006)		
Post	−0.069***		−0.070***		−0.068***		−0.070***	
	(0.006)		(0.006)		(0.005)		(0.006)	
Ln(Market value)	0.103***	0.108***	0.081***	0.076***	0.104***	0.107***	0.087***	0.075***
	(0.010)	(0.008)	(0.011)	(0.009)	(0.009)	(0.007)	(0.013)	(0.009)
B/M	0.000	0.004**	0.002	0.000	0.001	0.004**	0.005	0.002
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
RoE	0.001	0.001	−0.003	−0.002	0.002	0.002*	−0.001	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Volatility	−0.015***	−0.010***	−0.012***	−0.004	−0.016***	−0.011***	−0.010***	−0.003
	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)
Past return	0.002	0.002	0.002	0.003	0.002	0.003*	0.003*	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Turnover rate	0.012***	0.009***	0.013***	0.009***	0.009**	0.006**	0.012***	0.008***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.021***	0.022***	0.011***	0.013***	0.021***	0.023***	0.008*	0.012***
	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes	No	Yes	No	Yes
N	298,451	298,448	298,451	298,448	99,528	99,527	99,528	99,527
R2	0.225	0.341	0.336	0.439	0.367	0.484	0.541	0.637

A3. Additional analysis

A3.1 Placebo test: Firms with no 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 using European firms that have never been covered by any analyst during our sample period. If the general decrease in synchronicity is driven by analysts producing better-quality information, we should not observe a reduction in synchronicity for these firms. Table A9 shows that there is no significant change in return synchronicity for this set of European firms after the adoption of MiFID II, confirming our main analysis from an alternative perspective.

Table A9: Placebo test – Firms with no 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. *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. Firms with no analyst coverage during the entire sample period are included in the analysis. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Europe × Post	−0.014	−0.016	−0.018	−0.018
	(0.017)	(0.016)	(0.015)	(0.015)
Europe	−0.036	−0.043		
	(0.023)	(0.025)		
Post	−0.056***		−0.056***	
	(0.013)		(0.010)	
Ln(Market value)	0.087***	0.079***	0.065***	0.063***
	(0.011)	(0.011)	(0.016)	(0.016)
B/M	0.008***	0.007**	0.009	0.011
	(0.003)	(0.003)	(0.007)	(0.007)
RoE	−0.001	0.000	0.000	0.000
	(0.003)	(0.004)	(0.003)	(0.003)
Volatility	−0.013*	−0.003	0.004	0.009
	(0.007)	(0.007)	(0.007)	(0.005)
Past return	−0.002	0.002	0.004	0.006*
	(0.007)	(0.005)	(0.004)	(0.003)
Turnover rate	0.021***	0.019**	0.006	0.005
	(0.007)	(0.008)	(0.009)	(0.008)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	1,022	1,022	1,016	1,016
R2	0.451	0.532	0.789	0.820

A3.2 Stock price crash risk

In Section 4.1, we document that the introduction of MiFID II is associated with a significant decrease in stock return synchronicity, and the effect is significantly larger for negative returns. This can be interpreted as a reduction in exposure to systematic negative risk. Here, we explore an idiosyncratic component of negative 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).

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 A10. 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.

Table A10: 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. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	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
R2	0.033	0.301	0.048	0.291	0.015	0.300

A3.3 Variance ratio

We follow Boehmer and Kelley (2009) and Chen, Kelly and Wu (2020) to construct variance ratio to examine price efficiency. More specifically, because both positive and negative deviations of variance ratio form one represent stock price movement departing from a random walk, we use $|1-VR(n,m)|$ as a measure of market efficiency, where $VR(n,m)$ is the ratio of the return variance over m days to the return variance over n days, both divided by the number of the days. If prices follow a random walk, the deviation should be zero. Larger magnitude of this deviation reveals weaker market efficiency.

Table A11 shows that $|1-VR(n,m)|$ decreases for European firms after the adoption of MiFID II. We consider different choices of time horizons for measuring variance ratios within each year, such as *VR*(1,50), *VR*(1,100), *VR*(2,50), *VR*(2,100), *VR*(5,50), *VR*(5,100). The coefficients for $Europe \times Post$ are all negative, suggesting that market efficiency is improved for European firms following the introduction of MiFID II, though the results seem not quite statistically robust.

Table A11: Variance ratio and MiFID II

The dependent variable is |1−*VR(n,m)*|, where *VR(n,m)* is the ratio of the return variance over *m* days to the return variance over *n* days, both divided by the number of the days. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015-2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1) VR(1,50)	(2) VR(1,100)	(3) VR(2,50)	(4) VR(2,100)	(5) VR(5,50)	(6) VR(5,100)
Europe × Post	-0.004	-0.020*	-0.006	-0.021*	-0.005	-0.016
	(0.013)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)
Ln(Market value)	-0.106**	-0.097**	-0.064*	-0.055*	-0.013	-0.016
	(0.040)	(0.043)	(0.031)	(0.028)	(0.023)	(0.019)
B/M	-0.004	-0.004	-0.005	-0.003	-0.002	-0.003
	(0.008)	(0.008)	(0.006)	(0.007)	(0.006)	(0.005)
RoE	0.005	-0.007	0.002	-0.008	-0.003	-0.010**
	(0.009)	(0.005)	(0.008)	(0.005)	(0.005)	(0.004)
Volatility	-0.008	-0.013	-0.005	-0.008	0.002	-0.004
	(0.007)	(0.014)	(0.006)	(0.011)	(0.006)	(0.009)
Past return	0.009*	0.014**	0.007*	0.012**	0.004	0.008
	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
Turnover rate	-0.002	-0.006	-0.004	-0.008	-0.001	-0.007
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)
Ln(1+Analyst coverage)	0.013	0.004	0.009	-0.001	-0.002	-0.012
	(0.014)	(0.015)	(0.012)	(0.012)	(0.008)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	25,034	25,004	25,034	25,004	25,034	25,004
R2	0.268	0.256	0.261	0.255	0.253	0.249

A3.4 Price delay and MiFID II

To study the implications of MiFID II on 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 (which is the focus of our study). We first estimate the base model and the extended market model as follows:

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}, \tag{A1}$$

$$r_{i,t} = \alpha_i + \beta_i R_{m,t} + \sum_{n=1}^{5} y^n R_{m,t-n} + \varepsilon_{i,t} . \tag{A2}$$

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:

$$D1 = 1 - \frac{R^2_{Base}}{R^2_{Extend}} \tag{A3}$$

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

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

$$D2 = \frac{\sum_{n=1}^{5} n * |y_t^n|}{|\beta_i| + \sum_{n=1}^{5} |y_t^n|}. \tag{A4}$$

Unlike *D*1, which gives equal weights to all lags, *D*2 gives more weight to longer lags.

The final delay measure (*D*3) is a standard-error-adjusted version of *D*2. In other words, it gives more weight to more precise estimates.

$$D3 = \frac{\sum_{n=1}^{5} n * \frac{|y_t^n|}{se(\gamma_i^n)}}{|\beta_i| + \sum_{n=1}^{5} \frac{|y_t^n|}{se(\gamma_i^n)}}\ . \tag{A5}$$

The results presented in Table A12 show that MiFID II is associated with a significant decrease in the speed of stock price incorporating market-wide information. Note that this result does not contradict with our results based on return synchronicity, as the two capture very different aspects of information efficiency. Indeed, Busch and Obernberger (2017) discuss the distinction between "information content", i.e., the amount of firm-specific 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 firm-specific "information content" part, as captured by (low) return synchronicity with the market, while the price delay measures capture the market-level "price efficiency" part. Comparing these two sets of results provides an interesting insight: the adoption of MiFID II makes stock prices more informative to firm-specific information due to higher quality information production from equity analysts, at the cost of reducing the speed of price reaction to market-wide information. This could potentially due to the limited attention from general investors.

Table A12: Price delay and MiFID II

The dependent variables are proxies for price delays. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. *Industry-Year* fixed effects are based on two-digit NAICS codes. The sample period is 2015-2019. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	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
R2	0.398	0.693	0.440	0.712	0.376	0.647

A3.5 Future earnings return coefficient

Prior literature argues that the future earnings return coefficient can also capture price informativeness from a different perspective (e.g., Durnev, Morck, Yeung, and Zarowin, 2003). This is a sum of coefficients obtained from cross-sectional regressions in each year for different groups of firms. In other words, it is no longer a firm-level proxy. This nature makes this proxy not suitable for our agenda, because we focus on firm-level analyses. That being said, we still try to construct future earnings return coefficient at the industry level and examine whether price informativeness improves for European industries after the adoption of MiFID II. More specifically, we estimate the following cross-sectional regression within each 2-digit NAICS industry in each year:

$$r_{i,t} = \alpha_i + \beta_i \Delta E_{i,t} + \sum_{\tau=1}^{2} \gamma_\tau \Delta E_{i,t+\tau} + \sum_{\tau=1}^{2} \delta_\tau r_{i,t+\tau} + \varepsilon_{i,t} . \qquad \text{(A6)}$$

Here, $r_{i,t}$ is the annual stock return of stock i, and $\Delta E_{i,t}$ is the annual change in net income before extraordinary items dividend by the previous year's stock market capitalization. $\sum_{\tau=1}^{2} \gamma_\tau$ is the future earnings return coefficient for each 2-digit NAICS industry in each year. To make sure the coefficients represent reasonable estimates, we require each industry to have at least 10 (20) firms in column 1 (2) of Table A13. Note that our usual firm-level control variables, firm and industry-year fixed effects no longer apply in this small sample consisting of industry-year observations. Nevertheless, the coefficients for *Europe* $\times$ *Post* are positive, indicating potential increase in price informativeness for European industries after the adoption of MiFID II.

Table A13: Future earnings return coefficient and MiFID II

The dependent variable is future earnings return coefficient, constructed at the tow-digit NAICS level in each year. *Post* is a dummy that equals one from 2017 onwards, and zero otherwise. *Europe* is a dummy indicating firms based in Europe. The sample period is 2015-2019. Robust standard errors are shown in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1) At least 10 firms in each industry	(2) At least 20 firms in each industry
Europe × Post	0.844	0.554
	(0.614)	(0.502)
Europe	0.256	-0.0465
	(0.395)	(0.326)
Post	-0.663	-0.590*
	(0.434)	(0.353)
N	164	142
R2	0.039	0.024

A3.6 Stock return synchronicity by year

To confirm that our analysis is not simply capturing ongoing trends unrelated to MiFID II, we perform an analysis of stock return synchronicity, as well as the down-up difference in synchronicity, by year. We include all the interactions between *Europe* and the year dummies in our main regression and report the results in Table A14. 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 US 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.

The timing if the effect is notable as it helps as confirm that at least part of the effects we measure are directly attributable to changes in analyst incentives, as none of the other MiFID II rules related to trade reporting and dark pools could have plausibly affected the market in 2017.

Table A14: 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. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	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
R2	0.572	0.833	0.081	0.305

A3.7 Alternative correlation and R-squared specifications as measures of 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. 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.
- **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 US
- **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 US

In Table A15, 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.

Table A15: Alternative measures of stock return synchronicity

The dependent variable is shown above each column. *Corr.(country)* is the correlation coefficient of daily stock return with value-weighted return of all firms in each country. *Corr.(industry)* is the correlation coefficient of daily stock return with value-weighted return in each industry based on two-digit NAICS codes. *R-sqr.(market)* is the R-squared from a regression of daily stock return on daily market return. *R-sqr.(country)* is the R-squared from a regression of daily stock return on the value-weighted return of all firms in each country. *R-sqr.(industry)* is the R-squared from a regression of daily stock return on the value-weighted return of all firms in each industry based on two-digit NAICS codes. *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. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	Corr.(country) (1)	Corr.(industry) (2)	R-sqr.(market) (3)	R-sqr.(country) (4)	R-sqr.(industry) (5)	R-sqr.(market and industry) (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
R2	0.833	0.867	0.806	0.822	0.850	0.851

A3.8 Control for institutional ownership

One potential driver of stock return synchronicity could be the amount of passive investments (e.g., Anton and Polk, 2014). Therefore, in Table A16, we control for institutional ownership in our baseline regressions. Our baseline result on the reduction of return synchronicity for European firms after the adoption of MiFID II remains unchanged regardless of whether we control for institutional ownership.

Table A16: Controlling for institutional ownership

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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Europe × Post	-0.067***	-0.065***	-0.067***	-0.065***
	(0.007)	(0.007)	(0.007)	(0.007)
Europe	0.027***	0.052***		
	(0.007)	(0.011)		
Post	-0.064***	-0.065***		
	(0.004)	(0.004)		
Ln(Market value)	0.109***	0.107***	0.085***	0.078***
	(0.010)	(0.010)	(0.009)	(0.009)
B/M	0.002	0.005*	0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
RoE	0.003	0.002	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Volatility	-0.019***	-0.014**	0.003	0.004
	(0.005)	(0.006)	(0.003)	(0.003)
Past return	0.004**	0.005**	0.004***	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)
Turnover rate	0.011**	0.006	0.006***	0.006**
	(0.004)	(0.004)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.018***	0.012***	0.015***	0.013***
	(0.004)	(0.003)	(0.004)	(0.004)
Institutional Ownership		0.024***		0.019*
		(0.005)		(0.011)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	No	Yes	Yes
N	21,918	21,918	21,873	21,873
R2	0.567	0.573	0.837	0.837

Table A17: Controlling for illiquidity measure

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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1%, respectively.

	(1)	(2)	(3)	(4)
Europe × Post	-0.063***	-0.064***	-0.063***	-0.064***
	(0.006)	(0.006)	(0.007)	(0.007)
Europe	0.019**	0.019***		
	(0.007)	(0.007)		
Post	-0.066***		-0.070***	
	(0.005)		(0.005)	
Ln(Market value)	0.103***	0.105***	0.094***	0.079***
	(0.010)	(0.007)	(0.012)	(0.008)
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***	-0.010***	-0.009**	0.002
	(0.005)	(0.002)	(0.003)	(0.003)
Past return	0.005**	0.003**	0.005***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
Turnover rate	0.009**	0.005**	0.012***	0.007***
	(0.004)	(0.002)	(0.002)	(0.002)
Ln(1+Analyst coverage)	0.021***	0.023***	0.007*	0.013***
	(0.004)	(0.003)	(0.004)	(0.004)
Illiquidity Measure	-0.010***	-0.011***	-0.004	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
Firm FE	No	No	Yes	Yes
Industry-Year FE	No	Yes	No	Yes
N	25,070	25,070	25,043	25,043
R^2	0.554	0.610	0.807	0.833

2.5. Conclusion commentary

This research explores how MiFID II changes the aggregate level of information environment of European stock market following its implementation in 2018, through changing the incentives of sell-side analysts. It shows that although the overall number of sell-side analysts decreased after the implementation of MiFID II, the overall level of price informativeness increased.

There're also some specific points that need further discussing, or to be addressed in some future research regarding MiFID II.

The first specific point that needs to be further explored, is whether the change in synchronicity is driven by the change of disclosure requirements pre and post trades. MiFID II extends stricter disclosure requirements both pre and post trades to new products and venues, which include dark pool trading and OTC trading. Therefore, it's natural to assume that such stricter requirements on trade disclosures play a role in helping to improve the price informativeness of European stock markets. In robustness check A.2.1, I examine whether the change in price informativeness is driven by the MiFID II transparency requirements on MTFs (Multilateral Trading Facilities) by constructing a new subsample of European firms that don't have any MTF trading both before and after the implementation of MiFID II. Then I examine the change in synchronicity for the firms within this new sample and find similar results as in my main analysis in Table 2. This robustness check shows that the change in synchronicity is less likely to be driven by the new transparency requirements on MTF trading. Since such stricter requirements on trade transparency also apply to OTC trading, it's quite natural to consider the potential effect of more transparent OTC trading on the changes in synchronicity after the implementation of MiFID II. Constructing a new sample that doesn't include any firms with any OTC trading records both before and after the implementation of MiFID II, then re-examine the change of synchronicity for this sub-sample could be a starting point of easing this concern. But due to the lack of OTC trading data availability in both European stock market and U.S. stock market, constructing such sub-sample is currently not a practical option for me. Therefore, examining whether the stricter rules on OTC trading brought by MiFID II potentially drive the changes in synchronicity would have to be left for future research.

The second specific point needs to be addressed is how MiFID II changes the liquidity of European stock market, and whether such changes affect synchronicity. In previous literature, Gassen, Skaife, and Veenman (2019) find that stock price synchronicity measured by R-squared is biased downward because of stock illiquidity. Chan, Hameed, and Kang (2013) also find that illiquidity of stocks is negatively related to synchronicity. Therefore, it's natural to examine the changes in liquidity of stocks in European markets after MiFID II. Fang et el. (2020) discuss such relationship and find that the effect of MiFID II on the liquidity of European stock market is negative, partially filling this gap in literature. Despite the result of contemporary research on MiFID II and liquidity, it's necessary to examine whether the main result of my research still hold while controlling for liquidity measure. Therefore, I construct a new measure *Illiquidity* as in Amihud (2002), and re-examine the main test of my research while controlling *Illiquidity*. This new variable is defined as in the following equation:

$$Illiquidity_{i,y} = \frac{1}{Diy} * \sum_{t=1}^{Diy} |R_{iyd}| * Vol_{iyd}$$

In this equation, $Illiquidity_{i,y}$ measures the illiquidity of stock *i* on year y. Diy is the number of trading days for stock *i* in year *y* with non-zero trading volume. $|R_{iyd}|$ is the absolute daily return of stock *i* on day *d* of year y. Vol_{iyd} is the trading volume of stock *i* on day *d* of year y.

I then report the results of regression tests in Appendix Table A17 on page76 while controlling for *Illiquidity.* Although *Illiquidity* is negatively associated with synchronicity after MiFID II in all four columns, the coefficients of Europe × Post in all four columns remain negative and statistically significant. The results of such revised tests may contribute to easing the concern that the change in synchronicity after MiFID II is potentially driven by the change in liquidity.

The third specific point that needs to be addressed is the removal of firms in bottom decile in market cap, both in European stock markets and U.S. markets when constructing the sample. Firms that are too small in market cap are often very illiquid, and their co-movements with market are likely to be affected. It seems natural to remove the firms that are too small in market cap when constructing sample to start with, without losing generality. To ease the concern that my main results would be affected by such removal of smallest firms, I re-construct a new sample of all available European and U.S. firms without removing smallest firms and without propensity-score matching. The results of regression tests based on this sample is included in Appendix Table A4. The coefficients of all four columns remain negative and statistically significant, suggesting that my main results remain robust if the firms of smallest market cap are not removed.

The fourth specific point that needs to be addressed is the reason why firms covered by analysts with higher relative accuracy (i.e., those analysts that are better at doing their jobs) are also the firms that are more important to analysts and brokerage houses in general. In table 3, I construct a variable that measures the relative accuracy of an analysts based on all the firms he/she covers, namely *PMAFE*, in the same way defined as in Harford (2019). *PMAFE* measures how good an analyst is relative to all his/her peers covering similar portfolio of firms, based on EPS forecast accuracy. If a firm is covered by more analysts with lower PMAFE score (i.e., analysts that are relatively more accurate at estimating EPSs), this firm is usually considered as more important to brokerage houses and analysts. After all, brokerage houses tend to assign more skillful and experienced analysts that know better at their domain to cover important firms, which usually are the firms considered important by buy-side institutional clients. Buy-side institutions would naturally expect brokerage houses assign their best hands to work on forecasting EPSs for such firms. It would seem unwise for a brokerage house to assign analysts with poor performance record to cover a firm that attracts lots of attention from buy-side institutional investors.

In the next two chapters of this thesis, I focus my research on the sell-side analysts themselves, instead of financial regulations such as MiFID II. In chapter 3, I explore whether seniority of analysts could determine the overall performance of individual sell-side analysts as well as analyst teams. In chapter 4, I examine one of the key bases that chapter 2 was built on, namely the relationship between synchronicity and price informativeness.

Reference for conclusion commentary

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Chapter 3. Role of seniority in analyst teams: Evidence from China

3.1. Introduction

Sell-side analysts are widely considered as playing important roles within the financial markets worldwide. They dedicate their time and effort in conducting equity research when working for brokerage houses and communicate with their buy-side institutional clients regarding their recommendations and forecasts. With their reports and estimates, sell-side analysts serve as an important mean of information production and transmission as Brown, Call, Clement, and Sharp (2014) show. On one hand, sell-side analysts are responsible for collecting information from public listed firms by attending conference calls, conducting due diligence and analyzing quarterly or annually financial reports. On the other hand, recommendation reports are disseminated to institutional buy-side clients with adjusted EPS estimates and revised target prices, soon after these sell-side analysts fully digested the new information and modified their financial models.

Sell-side analysts serve as the channel of bringing the verified and digested new information into the stock market. Givoly and Lakonishok (1979) are among the pioneers to study sell-side analysts and showed that stock prices are significantly affected by the revisions of EPS estimates issued by sell-side analysts. Womack (1996) suggests recommendations and forecast reports from U.S. equity analysts could significantly affect the stock prices in U.S. market, providing evidence to show the existence of stock picking and market-timing abilities of analysts. Multiple prior research also explore the characteristics of sell-side analysts that would positively or negatively affect their performance and forecast accuracy. Clement (1999) provides evidence to show that analyst forecast accuracy is negatively associated with number of firms and industries covered by analysts, meanwhile positively associated with analyst experience and size of brokerage firm.

Brown et al. (2014) are among the first to study the differences between forecast performances of individual analysts and analyst teams, by showing that estimates issued by analyst teams are less accurate comparing to estimates issued by individual analysts, especially those individual analysts that work within analyst teams. Brightbill (2018) also documents that estimates issued by analyst teams are less accurate comparing to estimates issued by individual analysts before year 2000. Contrary to the traditional implicit assumption that forecast reports and estimates are in general issued by individual analysts, Fang and Hope (2021) find that more than 70% of the reports in U.S. market are issued by analyst teams instead. They further show that estimates and recommendations issued by analyst teams are in general more accurate and with greater impact in the stock market than those issued by their counterparts who work individually in the U.S. market.

Whether the performances (i.e., forecast accuracy and price impact on the market) of analyst teams are better than individual analysts are somewhat ambiguous given the seemingly contradictory previous literature. How characteristics of analysts that work within analyst teams affect their performances is also under-explored, especially the team structure, status, or seniority level of individuals within analyst teams. Groysberg, Polzer, and Elfenbein (2011) suggest that team performance benefits from the existence of star analysts within analyst teams to some extent, and this marginal benefit will soon vanish and even reverse if too many high-status analysts work together. Fang and Hope (2021) suggest that size of analyst teams, team members' abilities, and the level of diversity within teams are positively associated with accuracy of forecast estimates. He, Jackson, and Li (2020) explore Chinese sell-side industry and suggest that analyst teams with a clear hierarchy tend to perform better comparing to flat teams by issuing more accurate estimates that has stronger market impact. Ewens and Rhodes-Kropf (2015) study the performance and investment skills of Venture Capital partners as they move between different firms, providing an alternative and somewhat more direct method to study team members within an financial organization.

In this paper, I test the role of senior analysts within analyst teams and examine how seniority of individual analysts affect the performance of analyst teams using the data from Chinese stock market. Previous literature primarily focusses on how other factors affect the performance of analyst teams, such as hierarchy (i.e., He et al. 2020), high-status (i.e., Groysberg et al. 2011), diversity (i.e., Fang and Hope 2021). This research is different from previous research on at least two perspectives. First, seniority of analyst teams, proxied by number of reports issued or experience, is less explored by previous literature, especially when viewed as an aggregate attribute of an analyst team instead of each member within it. Second, this research study the difference in the role of seniority within analyst teams and individual analysts that work by themselves. Some other factors such as hierarchy and diversity are no longer applicable when it comes to individual analysts that work by themselves. Seniority on the other hand, when proxied by a continuous ranking variable, is worth exploring for individual analysts just as much as for analyst teams. It would be interesting to explore whether analyst teams with higher mean seniority ranking could outperform their individual counterparts in terms of market impact and forecast accuracy. It would be more interesting to compare the role of seniority for analyst teams and individual analysts that work by themselves and examine whether it remains the same for both groups.

The reason that I choose to focus on Chinese sell-side analysts instead of their U.S. or European counterparts, is primarily due to the data availability. The generally accepted database for information about U.S. and European sell-side analysts is the I/B/E/S, which doesn’t include the real names as well as the detailed team structure within analyst teams. Since I intend to focus my study on the team structure within sell-side analyst teams, it seems very hard to conduct my study on U.S. market or European market. On the contrary, conducting such study on Chinese market is much easier instead. The CSMAR database provides the key values and variables (i.e., EPS forecasts, Investment recommendation ratings etc.) of a collective of more than 560 thousand reports issued by more than 100 brokerage firms from 2000 to 2021 in Chinese stock market. Unlike I/B/E/S, CSMAR provides the full names and uniquely assigned codes of all analysts that signed their names on each equity report, providing a unique opportunity to study the relationship between analyst teams compositions and their performance on the stock market. Considering the availability of data regarding detailed team structure within analyst teams, I therefore choose to focus on Chinese stock market and Chinese sell-side analysts for this research. With the detailed basic background information of more than 9,000 unique sell-side analysts and a collective of north of 560,000 recommendation reports, I study the performance and market impact of analyst teams on the stock prices based on the characteristics of each report as well as analysts that issued it.

First, I examine the difference of market impact between upgrade revisions and downgrade revisions issued by sell-side analysts. Without any surprises, upgrade revisions issued by analysts yield significantly positive market impact whereas downgrade counterparts yield significant negative market impact, proxied by cumulative abnormal returns. Then I examine the difference of market impact between analyst teams and individual analysts by double sorting all reports based on their recommendation revision direction indicator (Upgrade/Downgrade) and analyst team/individual analyst indicator following the classic sorting method as in Fama and French (1992), Fama and French (1993), and Lin and Liu (2018). I then calculate the difference of cumulative abnormal returns for 3 trading days, 5 trading days, 10 trading days, and 30 trading days based on three factor model (Fama and French, 1993) for analyst teams and individual analysts. I find that recommendation changes issued by analyst teams generate higher market impact comparing to individual analysts that work by themselves, especially within the upgrade revision subsample. This result seems somewhat different from the results of Brown et al. (2014) and Brightbill (2018) at first, while supporting the findings of Fang and Hope (2021). Although Brown et al. (2014) and Brightbill (2018) mainly focus on forecast accuracy instead of market influence captured by cumulative abnormal returns, the larger market impact generated by recommendation revisions from analyst teams is still quite interesting and calls for attention. One possible explanation for this result is, of course, the difference in dataset. Both Brown et al. (2014) and Brightbill (2018) focus on U.S. analysts and U.S. stock market whereas my research focus on their Chinese counterparts. Another possible way to interpret this result may involve the process of information distribution of sell-side analysts. Buy-side institutional investors rely on phone-calls and face-to-face communications to gather information from sell-side analysts just as much as reading their reports, if not more. An analyst team consisting of multiple sell-side analysts could certainly disseminate more information in given period of time than an analyst that work alone when utilizing con-calls or roadshows, resulting in larger market impact.

Next, I examine how experience, or seniority of analysts affect market influence and overall performance separately for analyst teams and individual analysts that work by themselves. By sorting the reports by level of mean seniority and recommendation revision directions separately for analyst teams and individual analysts, I find that analyst teams with higher mean seniority level is associated with significantly greater market impact comparing to analyst teams with lower mean seniority level, while such phenomenon don't hold for analysts that work individually. I also examine the absolute forecast errors of EPS estimates using similar sorting method and find that analyst teams with higher average seniority tend to issue estimates with higher accuracy. But unlike for analyst teams, high seniority won't predict better estimates for individual analysts that work alone. This result partially supports the finding of He et al. (2020) that analyst teams with clear hierarchy perform better, although the definition of hierarchy in their research is quite different from the definition of seniority in this study. They define hierarchy as defined as the disparity in power or status within a group of analysts and partition analyst teams into hierarchical ones and flat ones, whereas I focus on the mean seniority of analyst teams captured by experience and number of reports issued. My results show that seniority, or experience level, of individual analysts don't matter too much regarding the market impact and performance when they choose to work alone. But when analysts work in teams instead, higher average seniority is positively associated with market impact and performance. It seems seniority of individual analysts plays a more important role and serves as a useful attribute in determining overall performance when analyst works in teams. This result is also partially in line with the result of Fang and Hope (2021). They also find that background variety is associated with better performance of analyst teams, using hand-collected analyst team-member data from U.S. market as well as their detailed personal background information from LinkedIn. But to my knowledge, seldom previous research directly examines the different roles of seniority within analyst teams and individual analysts. Considering the I/B/E/S doesn't disclose full information of all team members when issuing forecasts like CSMAR does, it's very hard to conduct similar tests examining the difference in analyst teams and individual analysts focusing on U.S. market or European market, when only relying on hand-collected analyst team data. After all, it's hard to be sure whether an analyst issuing forecast with only his/her name signed on the report is indeed an analyst that work alone, or is actually an analyst team failed to be recognized and identified. This lack of data could partially explain the lack of previous research on this topic in U.S. and European market.

To get more insights into the relationship between seniority and analyst team performance, I utilize team-change events (change of members within an existing analyst team) to directly study the change of relative forecast performance (i.e., PMAFE) before and after team change, inspired by Ewens and Rhodes-Kropf (2015). I carefully construct a subsample of estimates that only consists of estimates issued by analyst teams and only those experienced a team change in the recent year. Within this new sample, I further construct the treated group that meet the following conditions. Estimates in the treated group must be issued by an analyst team that experienced team change in the most recent year while covering the same target firm, newly joined by at least one senior analyst during the team-change, without any senior analysts in the previous year before the team change. This newly constructed treated group neatly replicates the team-change situations such that one or more senior analysts joined an existing analyst team that didn't employ any senior analysts in the previous year. If senior analysts joining a team of juniors could enhance their performance, estimates in the treat group should on average experience lower relative forecast error comparing to other estimates in the new sample. This is indeed true, since the treated group constructed here has significantly lower PMAFE comparing to other analyst teams with non-treated team changes (those regular team changes without recently joined by seniors). This test directly shows that an analyst team full of juniors joined by senior analyst(s) after a team change is associated with better relative performance.

The rest of this paper is organized in the following way. In chapter 3.2, I briefly review the past literature on sell-side analysts and analyst teams. In chapter 3.3 I carefully go through the data and methodologies of constructing sample and key variables. In chapter 3.4 I show the main results of this research, followed by robustness tests using a different measure of seniority in chapter 3.5. In chapter 3.6 I conduct additional analyses using team-change events to further understand the role of seniority in sell-side industry. In chapter 3.7 I concludes.

3.2 Literature review

In this section, I review some key literature that are related to the role of sell-side analysts in the financial market, as well as the impact of analyst team structures on its performance.

3.2.1 Role of sell-side analysts in financial markets

Sell-side analysts serve as an important mean of information production and communication in the stock market. They attend conference calls, meet with chief executives, digest publicly available documents of listed companies, and write reports to communicate with their institutional buy-side clients about the forecasts and recommendations they issue. Therefore, how sell-side analysts affect the performances of listed firms on the stock market through their coverage and reports had long been one of the key focuses of academic research.

Theoretically, Givoly and Lakonishok (1979) are the pioneers to investigate the relation between activities of sell-side analysts and the stock market prices. Based on the data between 1967 and 1974, they conduct empirical test and document abnormal returns exist after the earnings estimates. Womack (1996) examines the recommendations and reports issued by U.S. analysts. He finds that recommendation changes issued by sell-side analysts usually lead to permanent, instead of quickly mean-reverting, market reactions, suggesting recommendation changes provided by analysts contains valuable information that could benefit investment decisions. He also finds that sell-side analysts are reluctant to issue negative ratings instead of positive ratings, which is in line with the theory of Francis and Philbrick (1993). Hong, Lim, and Stein (2000) test the role of sell-side analysts in momentum strategy and find that momentum strategy works better for firms with lower analyst coverage while holding other factors fixed. They further show that firms covered by fewer analysts tend to react more sharply on bad news comparing to good news, and that sell-side analysts could affect stock market reactions in a more complex way than literature presumed in the past. Clement (1999) uses cross-sectional analysis to test the relationship between the performance of sell-side analysts and their characteristics. He concludes that experience and employer size could positively affect the performance (i.e., forecast accuracy) of analysts, meanwhile number of firms and industries assigned to cover (i.e., the "workload") could negatively affect the overall performance of analysts.

Barber, Lehavy, McNichols, and Trueman (2001) document that purchasing stocks that has the most favorable sell-side analyst recommendations consensus and rebalancing the portfolio daily could yield significantly positive returns. Meanwhile the positive abnormal return tends to diminish with less-frequent portfolio rebalancing. This shows that, to take advantage of abnormal returns generated from analyst recommendation consensus, investors may need to increase rebalancing frequencies. Doukas, Kim, and Pantzalis (2005) show that excessive analyst coverage leads to positive abnormal returns and overvaluations, which results in lower future abnormal returns. Their research is in line with the theory that sell-side analysts tend to raise investor optimism and leads to stocks trading above their fundamental values. Pursiainen (2021) finds sell-side analyst recommendations could predict stock returns in the European market, while being affected by cultural biases. Li, Liu, and Pursiainen (2022) show that although MiFID II implemented on 2018 reduced the number of sell-side analysts, it successfully decreased information asymmetry by providing more firm-specific information in the stock market through changes in analyst incentives.

3.2.2 Team structure and performance

Brown et al. (2014) are among the first to notice both analyst teams and individual analysts exists in the sell-side industry and examine their performances. They test the difference of analyst teams and individual analysts on their research quality and performance, proxied by earnings forecast accuracy. They find analyst teams in general underperform individual analysts, especially individual analysts within their teams, by documenting a larger forecast error. They also show that team forecasts are generally being issued in a timelier manner as well as resulting in larger market impact than those being issued by analysts that work individually. They also noticed that analyst teams and individual analysts tend to follow different types of firms. They find that analyst teams tend to cover larger firms and firms in greater distress comparing to individual analysts. In later research, Brightbill (2018) finds evidence to show more than three fourth of the investment recommendations issued by sell-side industry were actually issued by analyst teams instead of individual analysts. He also verifies the finding of Brown et al. (2014), and finds that analyst teams tend to underperform analysts that work individually, especially before year 2000. But this phenomenon is reduced by a series of regulations such as Regulation Fair Disclosure and the relative advantage of teamwork strengthens afterwards.

Contrary to Brown et al. (2014), Fang and Hope (2021) document that analyst teams generate more accurate estimates than individual analysts that work alone by using hand collected data from U.S. market. They verify that most of the reports and estimates in the U.S. market were indeed issued by analyst teams instead of individual analysts, in line with Brightbill (2018). Furthermore, they document stronger market reaction to recommendation revisions issued by analyst teams, partially in line with the conclusion of Brown et al. (2014). Utilizing detailed personal background information of analysts from LinkedIn, they also conclude that background variety is associated with better performance of analyst teams. Groysberg et al. (2011) find that analyst teams benefit from having high-status members, or stars, within the team up to a certain level. While He et al. (2020) suggest teams with clear hierarchy, which is defined as the disparity in power within analyst teams, tend to outperform the flat teams.

3.3 Data and methodology

In this section, I go through the data and methodologies involved in this research in detail. First, I show the datasets I used in this research and go through the process of sample construction. I then explain how the key variables in the empirical tests are constructed, before going through the detailed methodologies of empirical research and test designs.

3.3.1 Data and sample construction

The main datasets involved in this research are CSMAR analyst forecast dataset, CSMAR financial statements dataset, and CSMAR stock market daily trading dataset. The CSMAR analyst forecast dataset consists of more than 564 thousand sell-side issued reports with yearly earnings per share (EPS) estimates and investment recommendations from 2000 to 2021 (June 2021 in this research). CSMAR financial statements dataset contains financial reporting variables such as total assets, total liabilities, book value, return on equity, actual EPS for all listed A-shares and B-shares in Chinese stock market for each financial year. CSMAR stock market daily trading dataset contains the daily stock prices and returns of all A-shares and B-shares that trades in Chinese stock market, as well as daily closing prices of major indices such as the CSI 300 index. The datasets involved in this research share the same key linkage variables such as the firm ID (Stkcd), broker ID (B_code), analyst code (A_code), and sell-side report ID (Report_id).

I start with the full sample of sell-side analyst reports issued by more than 100 brokerage houses and 9,774 unique analysts from 2000 to 2021, consisting of roughly 564 thousand unique reports. Each of these reports are either written by an individual analyst, or an analyst team consisting of more than one analyst. Around 93% of all reports issued a “buy” or “strong buy” recommendation, in line with the finding of Womack (1996) that analysts are reluctant to issue neutral and negative ratings. In terms of issuance by analyst teams and individual analysts, more than 58% of all reports were issued by individual analysts that work by themselves and less than 42% of all reports were issued by analyst teams. Of all the 564 thousand unique reports issued, around 8 thousand were without valid analyst code and hence unable to be identified with the issuing analysts. I therefore remove these reports from the sample. The remaining 556 thousand reports are further categorized into five different types based on their recommendation revision indicator, which consists of “Upgrade”, “Remain”, “Downgrade”, “Initial Coverage”, and “Re-coverage”. I include the reports with first three types of recommendation revision indicator and focus on the “Upgrade” and “Downgrade” groups since they presumably contain more useful information. Eventually the sample consists of around 420 thousand unique reports, and thus observations, at this stage. This includes around 14 thousand “Upgrade” observations, 400 thousand “Remain” observations, and less than 9 thousand “Downgrade” observations. Based on this sample, I conduct double sorting and test the difference of analyst (teams) performance with different seniority rankings.

The sample in the team-change related tests (see Chapter 3.6) is different from the previous sample. I identify a sub-sample of reports that are issued by analyst teams right after experiencing a team change. Since the dependent variable is PMAFE (see, for instance, Harford, Jiang, Wang, and Xie, 2019), a relative measure of forecast accuracy that’s comparable across analyst teams, I filter the observations based on the following criterions to make sure all observations are comparable within this team-change sample. To be included in this sample, a report must be the last valid report issued by a brokerage house for a firm-year combination before the actual EPS announcement so that the estimate accuracy is comparable across analyst teams covering the same firm-year. Next, I only include the reports issued by analyst teams that involves team member changes comparing with previous year. That is to say, this sample only includes reports issued by analyst teams that experienced team change in the most recent year. I further filter the sample by requiring reports to be issued by analyst teams instead of individual analysts both for the current financial year as well as for the previous financial year. In this way, reports are issued by analyst teams both before and after team-change events and are thus comparable. Eventually, this sample consists of around 19 thousand valid observations containing EPS estimates issued by only analyst teams with comparable PMAFE values that experienced team-change events in the most recent year.

3.3.2 Variables in this research

In this section I introduce the process of constructing the variables in this research. Abnormal returns are calculated based on two different methods. I first calculate the abnormal return based on the Fama-French 3 factor model as in Fama and French (1993), with sensitivity coefficients (β) calculated based on a 3-month rolling window. Then I also calculate a second measure of abnormal return by taking the difference of individual stock daily return and CSI 300 index daily return, where CSI 300 index is a widely accepted market index tracking the returns of 300 large-cap and mid-cap stocks listed in Shanghai and Shenzhen stock exchanges. Since CSI 300 index represent roughly 70% of market cap in whole Chinese stock market, it serves as a good benchmark when calculating abnormal returns.

Absolute forecast error is defined as taking absolute value of the difference of EPS estimate and actual EPS, then scaled by share price. In this research, I choose to use the share price of last trading day of each financial year to avoid using future information by mistake. If an analyst or analyst team issued more than one EPS estimate for a firm-year combination, which is usually the case, I keep the most recent valid estimate that's issued before the actual EPS announcement date. I also filter the estimates and only include estimates made within the current financial year, to avoid including outdated estimates that are not comparable with up-to-date forecasts. At this step, the number of estimates included in the sample is around 378 thousand.

I then follow Harford et al. (2019) to construct a relative forecast performance measure, namely PMAFE, as the dependent variable in some later regression tests. PMAFE is defined as:

$$PMAFE = \frac{(AFE - MAFE)}{MAFE} \qquad (1)$$

AFE is absolute forecast error of the estimate, and MAFE is the mean of all absolute forecast error values from all the analyst or analyst teams covering the same firm-year. PMAFE measures how good an analyst or analyst team is by comparing their accuracy with the mean accuracy of all other analysts covering this firm-year combination. If an analyst or team is performing very well comparing to pairs covering the same firm in the same year by achieving lower AFE, then PMAFE should be negative and approach to -1 according to equation (1). PMAFE is a measure of relative performance of analyst or analyst teams by comparing AFEs with their competitors, therefore it's a comparable measure even across time and target firms.

In this research, seniority is defined as a measure of how experienced or "seasoned" an analyst is comparing to all other active analysts in the same quarter. Seniority ranking is calculated on a quarterly basis for each unique analyst and this ranking would remain unchanged throughout the whole quarter, until an updated ranking becomes available at the beginning of next quarter. I construct seniority base on two methods, weighted number of reports issued and number of days as sell-side analyst. For each quarter after 2006, I construct *Seniority. (Reports)* as the percentile ranking of weighted sum of reports issued by the analyst during his/her entire career till the beginning of quarter among all active analysts. "Weighted number of reports" here means that, if a report is issued by an analyst team consisting of N analysts instead of an individual analyst alone, it will account for 1/N towards his/her total number of reports. Analysts accomplished more reports till the beginning of each quarter will receive a higher-ranking percentile score, and thus considered as more senior than analysts receiving lower ranking scores in this particular quarter. As for the second measure *Seniority. (Exp)*, I calculate days of experience of an analyst by calculating the number of days between the date of his/her first report and the first date of the current quarter. Analysts served longer days in the sell-side industry are considered as more senior than their counterparts served shorter period in the industry, and thus will be assigned a higher percentile ranking at the beginning of quarter.

Control variables in the regression tests, such as market size, return on equity, turnover rate, return standard deviations, analyst coverage, past return, book-to-market ratio, are defined, calculated, winsorized, and standardized in the similar way as in Lin and Liu (2018) as well as in Li et al. (2022).

3.3.3 Methodology and empirical test design

In this section, I introduce the methodologies involved in the empirical tests of this research. Following similar cross-sectional sorting method as in Fama and French (1992), Fama and French (1993), and Lin and Liu (2018), I sort the sell-side forecasts by seniority ranking and recommendation revision groups for analyst teams subsample and individual analysts subsample separately.

First, I separate the full sample into reports issued by analyst teams and reports issued by individual analysts. Then within each subsample, I sort it into three portfolios based on seniority ranking scores with cutoff points equal to 33% and 67%. I then further sort each portfolio by recommendation revision group, which consists of “Upgrade”, “Remain”, and “Downgrade”. Eventually each sub-portfolio contains roughly similar number of observations. I then conduct t-test to examine the difference of 3 days, 5 days, 10 days, and 30 days accumulated abnormal returns between sub-portfolios with highest seniority ranking and lowest seniority ranking within each recommendation revision group. In the following step, I conduct t-test to examine the difference of absolute forecast error means between sub-portfolios as in the previous step.

In the later empirical analyses, I examine the relation between cumulative abnormal returns and seniority ranking using regression tests. To be specific, I conduct the following regression test specified as:

$$CAR(T) = \alpha_0 + \beta \times Seniority_{ranking} + \gamma \times X + \varepsilon \quad (2)$$

CAR(T) is cumulative abnormal return calculated using either Fama-French 3 factor model or CSI 300 index for T trading days after the issuance of each estimate. In my research, I test accumulated abnormal returns for 3 days, 5 days, 10 days, and 30 days in the regression analysis. Seniority ranking is the mean seniority percentile ranking of all the analysts within the analyst team (or simply the seniority ranking of individual analyst if not an analyst team) when issuing the report and recommendation, based on either weighted report method or experience method introduced in section 3.2. X is the vector of controls, including market size, book-to-market ratio, past return, turnover rate, analyst coverage, return standard deviation, and return on equity. Figures for 30 days accumulated abnormal returns are also provided. ε is the error term.

In empirical analyses examining the relation between analyst teams' performance and seniority, I conduct the following regression test specified as:

$$PMAFE = \alpha_0 + \beta \times Seniority_{ranking} + \gamma \times X + \varepsilon \quad (3)$$

PMAFE is a measure of relative performance of analyst teams (or individual analysts) comparing to all other analyst teams covering the same firm in the same financial year. PMAFE is defined in section 3.2. Seniority ranking is the mean seniority percentile ranking of all the analysts within the analyst team (or simply the seniority ranking of individual analyst if not an analyst team) when issuing the report and recommendation, based on either weighted report method or experience method introduced in section 3.2. X is the vector of controls, including market size, book-to-market ratio, past return, turnover rate, analyst coverage, return standard deviation, and return on equity. ε is the error term.

3.4 Main results

In this section, I introduce the results of my main empirical analyses. I show the results of sorting in the section 3.4.1, and results of regression analyses in section 3.4.2.

3.4.1 Examine the role of seniority with sorting

I first examine the Fama-French 3 factor model (Fama and French, 1993) accumulated abnormal returns for Upgrade subsample, Remain subsample, and Downgrade subsample separately. As Table 1 shows, Upgrade estimates are associated with significant positive market impact whereas downgrade estimates are associated with significant negative market impact. This verifies that recommendation revisions issued by sell-side analysts contains important information that could indeed affect stock market prices. I go on to examine whether analyst teams outperform or underperform individual analysts in terms of market impact, a somewhat less-explored question given contrary previous literature.

In Table 2 and Figure 1, it's clear that upgrades issued by analyst teams generate significantly larger price impact comparing to upgrades issued by individual analysts. Whereas the difference between market impact of downgrades issued by analyst teams and individual analysts is not significant. It seems to show that stock market is more sensitive to upgrades issued by analyst teams, probably because analyst teams could communicate with all their buy-side institutional clients in a timelier manner than individual analysts that work by themselves.

In Table 3 and Figure 2, I examine the result of sorting by recommendation revision direction groups and seniority ranking groups separately for analyst teams and individual analysts. The cumulative abnormal returns in this table is based on Fama-French 3 factor model, and seniority ranking is calculated based on number of reports issued as described in section 3.3.2. Panel A shows the sorting result for reports issued by analyst teams. As panel A shows, "Upgrade" recommendations issued by analyst teams in the higher seniority ranking portfolio generate significantly larger market impact than those issued by analyst teams in lower seniority ranking portfolio. Whereas difference in "Downgrade" recommendations issued by analyst teams with higher seniority ranking and analyst teams with lower seniority ranking is not statistically significant. This result shows that stock market is more sensitive to upgrades issued by analyst teams with higher average seniority ranking. Panel B of Table 3 shows the sorting result within individual analysts' sample. Panel B shows that seniority ranking won't affect market impact of recommendation revisions issued by analysts that work individually. Overall, Table 3 seem to suggest that seniority ranking does affect level of market impact when analysts work together in teams, but not so when analysts work individually.

In Table 4, I examine the result in Table 3 with a different method to calculate cumulative abnormal returns. In Table 4, abnormal return is defined as the difference of individual stock daily return and CSI 300 index daily return. As section 3.3.2 explains, CSI 300 index covers all major firms in Chinese stock market listed in Shanghai and Shenzhen stock exchanges, representing around 70% of total market cap. The results in Table 4 further confirm the conclusion of Table 3, showing even stronger results in t-tests within analyst teams' subsample.

Despite market impact, absolute forecast accuracy is another important dimension to measure performance of analyst teams or individual analysts. Therefore, in Table 5, I examine the relationship between seniority level and absolute forecast accuracy within sub-samples using similar sorting method. Column (1) shows that absolute forecast error is significantly lower for analyst teams with higher average seniority ranking than analyst teams with lower average seniority ranking, where seniority ranking is measured by number of reports issued as in section 3.3.2. The result remains similar if measure of seniority changes from number of reports to days of experience, as column (2) shows. Although the result is significant within the analyst team sub-sample, it's not obvious that seniority has any similar impact on absolute forecast error within individual analysts' sub-sample. The t-statistics in both column (3) and (4) are insignificant.

Taken together, Table 3, 4 and 5 show that seniority ranking of analysts play an important role and could significantly increase the performance when analysts work in teams. But when analysts work alone, seniority doesn't seem to make much difference regarding their performances. These results seem to suggest that seniority is a valuable and important attribute of sell-side analysts, but only kicks in when analysts work in teams.

3.4.2 Examine the role of seniority with regression tests

In this section, I examine the role of seniority in the performance of sell-side industry by using various regression tests. Table 6 shows the relationship between mean seniority and market impact within the "Upgrade" revision sample, separately for analyst teams and individual analysts. The dependent variable is cumulative abnormal returns (CARs) for 3, 5, 10, and 30 trading days using abnormal returns calculated from 2 different methods, the Fama-French 3 factor model method and CSI 300 index benchmark method introduced in section 3.3.2. The independent variable of interest is mean value of seniority ranking for each analyst team (or individual analyst) based on number of reports issued. I include 7 control variables and 2 fixed effects as shows in the bottom of each column, in a similar fashion as in Li, Liu, Pursiainen. (2022). In Panel A, even though not all columns yield significant result, the pattern in general shows seniority ranking is positively associated with market impact within analyst teams' sub-sample, and that upgrades issued by analyst teams with higher mean seniority ranking tend to generate higher positive market impact. In Panel B, none of the coefficients in any of the 8 columns is statistically significant, with a few of them even being negative. This table seems to further confirm the conclusion of Table 3.

The next table shows the relationship between PMAFE, the relative performance measure of analysts (see Harford et al., 2019), and mean seniority separately for analyst teams subsample and individual analysts' subsample. In Table 7, the dependent variable is PMAFE, defined as in section 3.3.2. In column (1) to (3) of both Panel A and Panel B, independent variable of interest is seniority ranking by number of reports issued as defined in section 3.3.2. In column (4) to (6), the independent variable of interest is seniority ranking defined by number of days an analyst served in sell-side industry. As in the previous table, I include 7 control variables and 2 fixed effects. Although coefficients for seniority are both significantly negative in both Panel A and Panel B, suggesting seniority is negatively associated with PMAFE for both analyst teams sub-samples, the coefficients are almost twice as large for team sub-sample. Since lower PMAFE indicates better relative forecast estimates, this table shows seniority is positively associated with analyst relative forecast performance, especially within analyst teams' sub-sample.

3.5 Robustness check

In this section, I use days of experience in the sell-side industry as a second measure of seniority to conduct robustness tests. Days of experience is calculated as the number of days between the first date of current quarter (when seniority is being measured) and the date when first report is being issued by the analyst. For instance, if an analyst has issued his/her first report on January 1st 2005, days of experience as of January 1st 2008 would be 1095 days. Seniority ranking for each unique analyst on each quarter is measured based on such days of experience, instead of weighted number of total reports issued.

I then reconduct the tests in Table 3, Table 4, and Table 6. As Table 8 shows, upgrade revisions issued by analyst teams with higher average seniority ranking generally yield higher positive market impact than upgrade revisions issued by their lower mean seniority counterparts. Similar effect is not observed in individual analyst sub-sample. Table 9 verifies the result of Table 8, using CSI 300 index as benchmark when calculating cumulative abnormal returns. The t-statistics is even larger than what Table 8 shows, indicating an even stronger effect. Finally, Table 10 verifies the regression test results of Table 6. As Panel A of Table 10 shows, seniority ranking is positively associated with cumulative abnormal returns for upgrades issued by analyst teams, but similar effect is not observed for upgrades issued by individual analysts as none of the coefficients for seniority are positive and significant in Panel B.

These three robustness tests indicate that using an alternative measure of seniority ranking will not change the basic results showed in the previous section. Seniority ranking is positively associated with better estimates and larger market impact within analyst teams' sub-sample, but less so in the individual analyst's sub-sample.

3.6 Additional analyses

To further understand the role of seniority in sell-side industry, especially how senior analysts directly affect the relative forecast accuracy of analyst teams, I design the following tests to directly examine the relationship between seniority and PMAFE using team-change events inspired by Ewens and Rhodes-Kropf (2015).

Structural changes of analyst teams pose an opportunity to directly study how senior analysts could positively (or negatively) affect the forecast accuracy of an existing analyst team covering the same listed firm. According to the results of previous tests in section 4, an analyst team consisting of a bunch of junior analysts should experience an overall increase in forecast accuracy when joined by one or more senior analysts. To make sure forecast accuracy is comparable before and after the team-change events, I study PMAFE, the relative forecast accuracy measure, to compare the before and after team-change relative performance of an analyst team against its peers covering the same listed firm.

3.6.1 Team-change study: sample and variables

Since I intend to study team-change events, I start with the filtered analyst teams' sub-sample consisting of 138 thousand valid estimates with unique report IDs. All estimates included in this sub-sample are issued by analyst teams with at least 2 analysts. Chinese sell-side analysts frequently issue EPS estimates for the following 3 financial years within the same report, I hence need to adjust the sample by keeping the EPS estimate for the most recent year to make sure estimates and forecast accuracy are comparable across teams. After all, it's not fair to compare the estimate provided by a certain analyst team 3 years ago with estimate provided by another team 15 days ago.

I further filter the data by keeping observations issued by analyst teams that consequently covers the same firm non-stop so that team-change is meaningful (otherwise that will be 2 completely different teams instead of one team experiencing team-change). For instance, if a broker issued an estimate for a firm in 2005 and dropped coverage ever since, only to re-initiated coverage again in 2009, this observation shouldn't be included in the sample. Eventually, I'm left with about 19 thousand estimates issued by analyst teams that experienced a team-change in the past financial year covering the same listed firm. Note that all these analyst teams consist of at least 2 members before and after the team-change events and issued comparable up-to-date EPS estimates on the same firm.

The final sample for team-change study consists of only observations (reports with EPS forecasts) that meet the following criterions. First, an analyst team issued valid and up-to-date EPS forecast for a firm X in certain financial year T in a unique report. Second, this particular analyst team experienced a team-change right after, before issuing the next EPS forecast for firm X's financial year T+1. Third, this particular analyst team issued a valid and up-to-date EPS forecast for firm X's financial year T+1 after the team-change in a different report with unique report ID. This is a neat sample consisting of only reports issued by analyst teams that experienced team-change events and continued covering the same firm, with comparable and valid PMAFE values.

The team-change subsample can be further categorized into 4 different classes by using 2 dimensions, before/after team-change and with/without senior analysts. I use B to indicate "before team-change event" and A to indicate "after team-change event", whereas using 0 to indicate "no senior analysts in team" and 1 to indicate "at least 1 senior analyst in team". Senior analysts are defined as the analysts received top 33% seniority ranking percentile based on number of reports issued at the beginning of each quarter. To put it in another word, only the top 1/3 of all active analysts could be considered as senior analysts in any given quarter based on their seniority rankings so far. Then the team-change subsample can be categorized into 4 classes based on these two dimensions.

B0_A0 indicates an estimate made by an analyst team with no senior analysts on board before and after team-change events. B0_A1 indicates an estimate made by an analyst team joined by at least 1 senior analyst after team-change event, but without any senior analysts before team-change. B1_A0 indicates an estimate by an analyst team without any senior analysts, which used to have at least 1 senior analyst on board before team-change. B1_A1 indicates and estimate made by an analyst team with senior analysts before and after team-change event. Since I intend to study how senior analysts affect performance of analyst teams using team-change events, B0_A1 and B1_A0 are the groups of interest.

3.6.2 Team-change study: PMAFE and seniority

I start with examining the relationship between seniority and PMAFE by running regression tests as in Table 11. Dependent variable in this test is PMAFE, as defined in section 3.3.2. BO_A1 and B1_A0 are dummy variables indicating the groups of observation of our interest defined in section 3.6.1. BO_A1 equals to 1 if an estimate is issued by an analyst team without senior analysts on board before the team-change and joined by certain senior analyst(s) during the team-change, and 0 otherwise. On the contrary, B1_A0 equals to 1 if an estimate is issued by an analyst team that with senior analysts before the team-change event but without senior analysts after the team-change event, and 0 otherwise. As Table 11 shows, coefficients of BO_A1 is statistically significant and negative, suggesting senior analysts joining a team of juniors is associated with higher relative forecast accuracy of the team comparing to its peers after the team-change. What's more, insignificant yet positive coefficients of B1_A0 suggest senior analysts leaving a team after team-change is associated with inferior performance relative to peers.

I continue to explore the relationship between sum of senior analysts within an analyst team and its relative performance by running the regression test in Table 12. In this regression test, the dependent variable is still PMAFE while Sum_Senior is the total number of all senior analysts within an analyst team. As this table shows, total number of senior analysts within an analyst team is negatively associated with PMAFE, indicating a positive association with relative performance against its peers covering the same firm.

Finally, I investigate how number of senior analysts affect relative performance while requiring number of senior analysts before team-change to be zero. In Table 13, the coefficient of interaction term B0*Sum_Senior is negative and statistically significant while controlling for 7 control variables and 2 fixed effects. This shows that for those analyst teams don't have any senior analysts before team change, number of senior analysts is negatively associated with PMAFE, indicating an improvement of relative forecast accuracy comparing with peers as number of seniors on board increases.

3.7 Conclusion

In this research, I find evidence to show that analysts perform better when work in teams by using Chinese stock market data and over 560 thousand sell-side reports from 2000 to 2021. I also study the role that seniority plays in determining the performance and market impact of analyst teams and individual analysts. By double sorting on recommendation revisions directions and seniority rankings, I show that analyst teams with higher mean seniority significantly outperform individual analysts with higher market impact and lower forecast error. But I don't observe similar phenomenon for individual analysts that work by themselves. These results indicate that seniority plays important roles in determining the overall performance of analyst teams. It seems seniority of analysts is an important and valuable attribute only when analysts work together.

In additional analyses, I further enhance my main results by using team-change as opportunity to study the role of senior analysts within an analyst team. By exploring the relationship between seniority and PMAFE in team-change subsample, I find evidence to show senior analysts could significantly improve the relative forecast accuracy of an existing analyst team. My study shows seniority of sell-side analysts is an important determining factor of analyst teams' overall performance. However, it matters less when analysts work alone by themselves. As for recommendation of future work, it would be an interesting point to explore whether part of my results is driven by star analysts. As Xu et al. (2013) show, stocks covered by star analysts experience decreases in return synchronicity measured by R-squared, instead of increases. Their result shows that star analysts and non-star analysts could generate different effect during information production process. Controlling for star analysts could further enhance most of our main results, since star analysts are in general more likely to be senior analysts.

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Figure 1: CARs for 30 trading days

Cumulative abnormal returns for 30 trading days. Abnormal returns are calculated based on Fama-French 3 factor model as explained in section 3.2. All sell-side reports are sorted into 3 groups by their recommendation revision variables. As this figure shows, upgrades issued by analyst teams have greater positive market impact in general compared with upgrades issued by individual analysts.

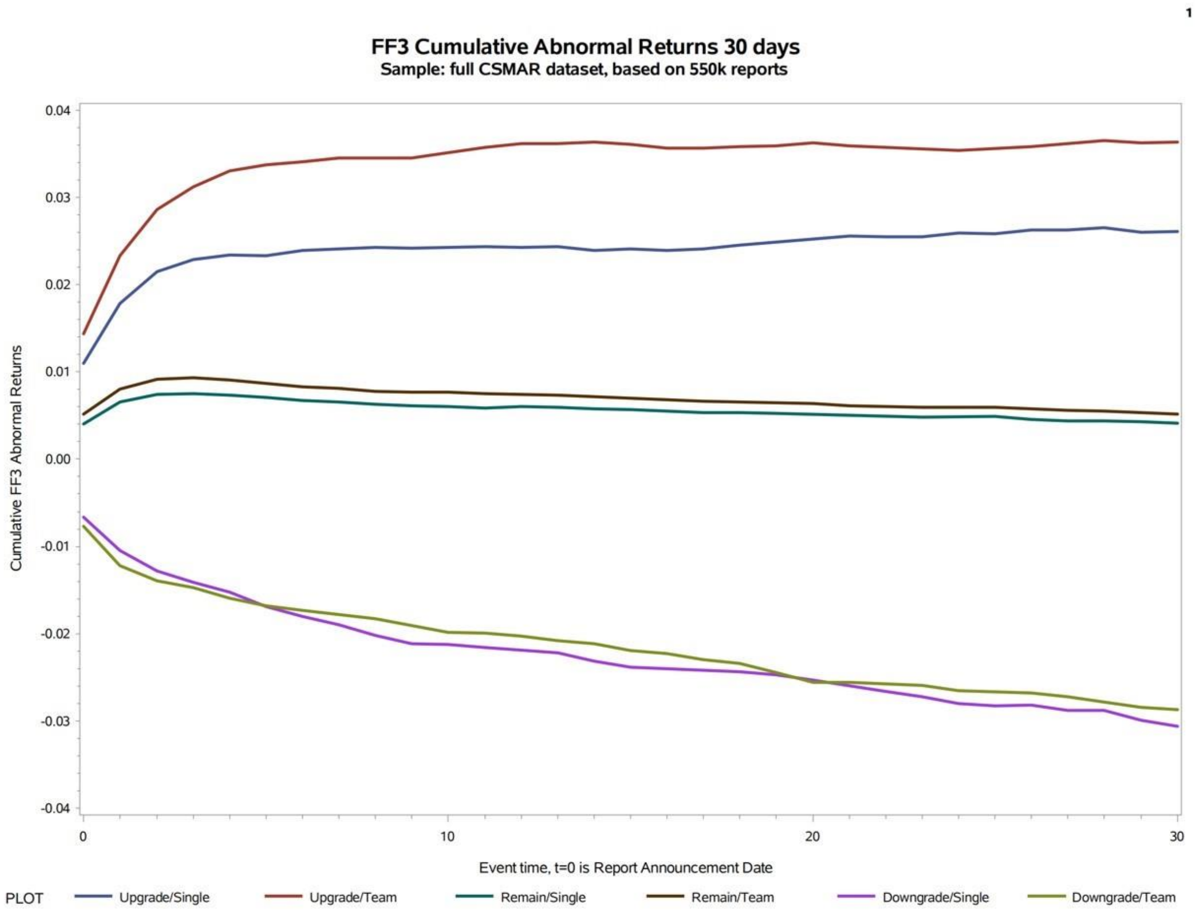
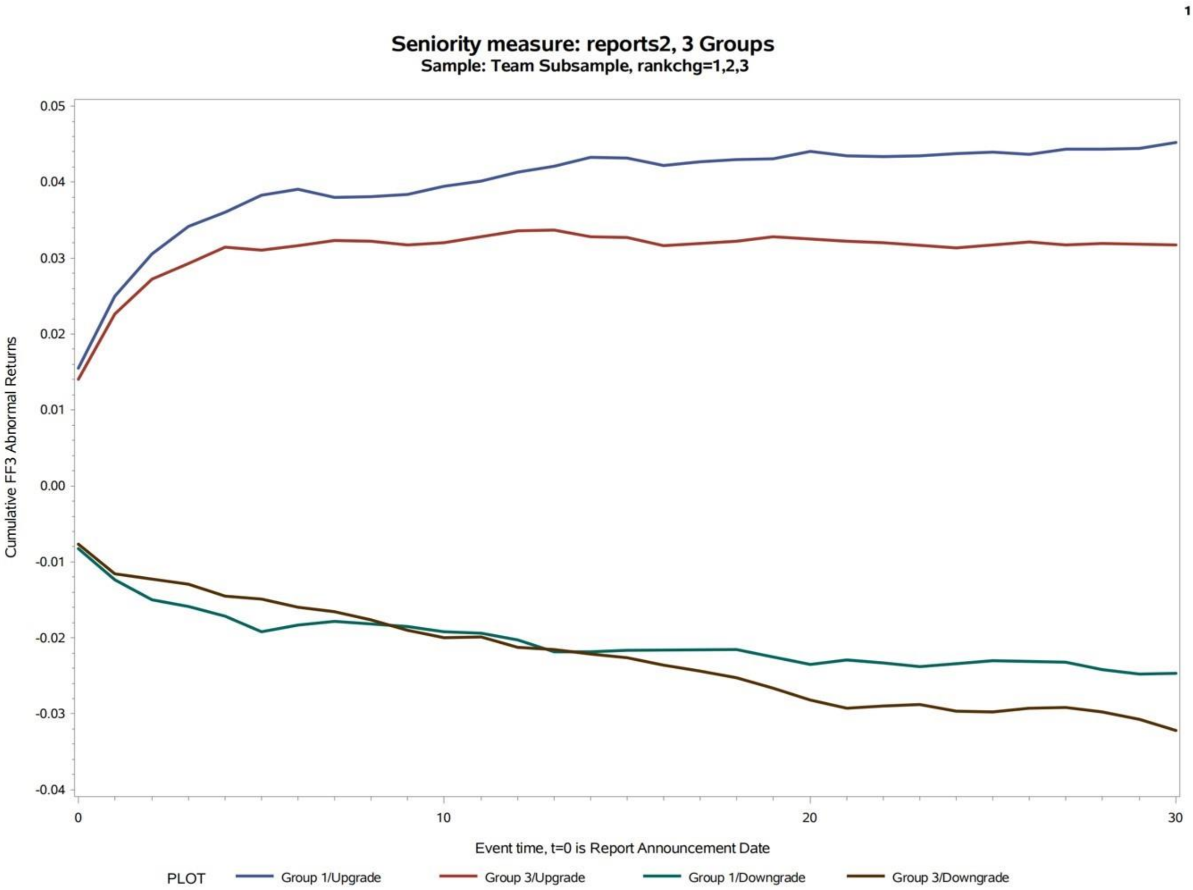


Figure 2: Analyst Teams versus Individual Analysts

Cumulative abnormal returns for 30 trading days. Abnormal returns are calculated based on Fama-French 3 factor model as explained in Section 3.2. All sell-side reports are sorted into 3 groups by their recommendation revision variables. Panel A shows the result for analyst teams sub-sample. Panel B shows the result for individual analysts' sub-sample. Group 1 indicates the portfolio with highest seniority ranking, whereas group 3 indicates the portfolio with lowest seniority ranking. Seniority is measured by total number of weighted reports as explained in section 3.2.

Panel A: CARs for Upgrades and Downgrades Issued by Analyst Teams



Panel B: CARs for Upgrades and Downgrades Issued by Individual Analysts

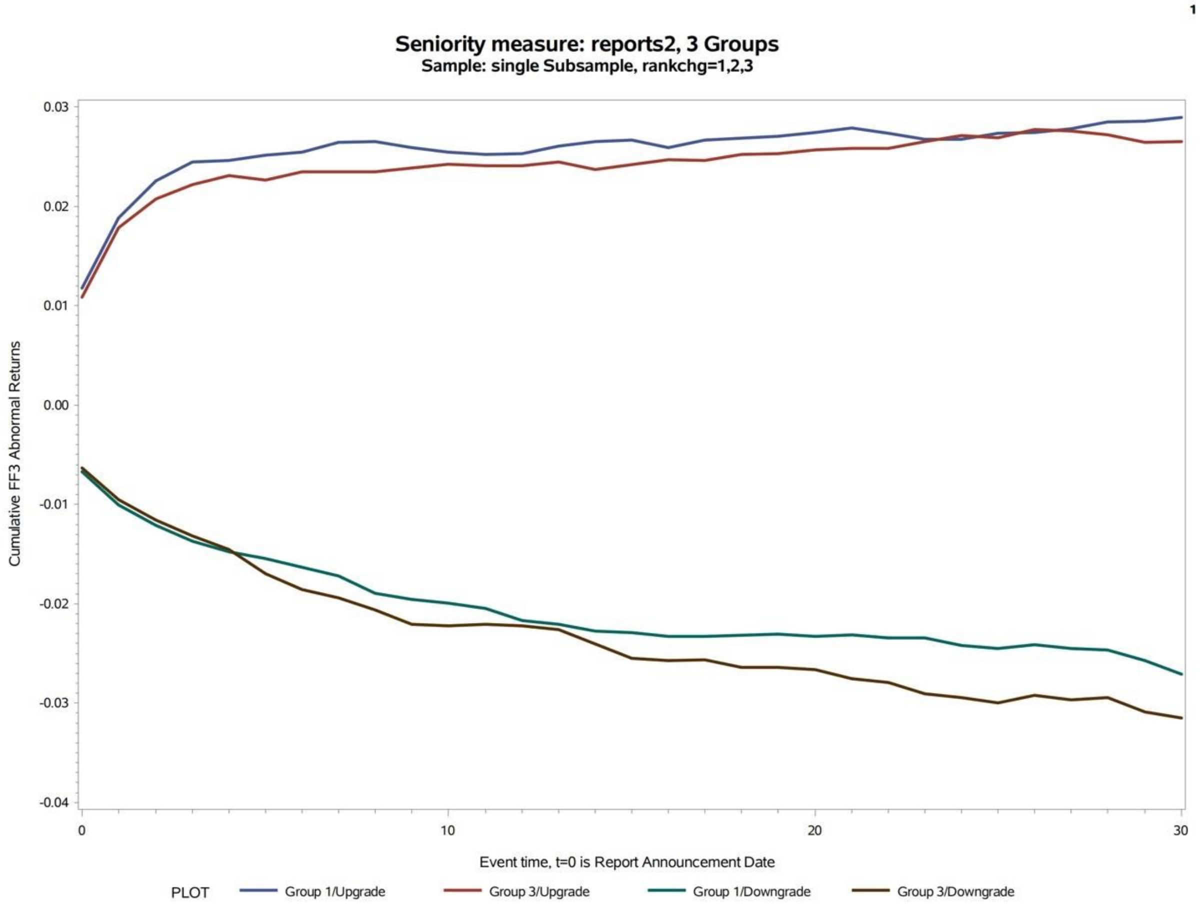


Table 1: CARs by Recommendation Revision Directions

Cumulative abnormal returns are calculated based on Fama-French 3 factor model as explained in section 3.2. All sell-side reports are sorted into 3 groups by their recommendation revision directions, including Upgrade, Remain, and Downgrade. AR_3, AR_5, AR_10 and AR_30 are cumulative abnormal returns for 3, 5, 10, and 30 trading days.

Revision Direction	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	Mean Value	0.0241	0.0269	0.0279	0.0295
	T-statistics	44.82	40.53	33.27	24.41
	N	13635	13667	13709	13829
Remain	Mean Value	0.0081	0.008	0.0067	0.0045
	T-statistics	98.12	80.8	53.14	22.48
	N	388992	389830	391177	393930
Downgrade	Mean Value	-0.0131	-0.0153	-0.0201	-0.0293
	T-statistics	-23.58	-23	-23.25	-21.63
	N	8495	8518	8552	8608

Table 2: CARs by Recommendation Revision Directions and Team Indicator

Cumulative abnormal returns are calculated based on Fama-French 3 factor model as explained in section 3.2. All sell-side reports are sorted into 3 groups by their recommendation revision directions, including Upgrade, Remain, and Downgrade, then sorted again by team indicator. Team is a dummy variable indicating whether a report is issued by an analyst team or an individual analyst. AR_3, AR_5, AR_10 and AR_30 are cumulative abnormal returns for 3, 5, 10, and 30 trading days.

Revision Direction	Team	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	Team=0	Mean Value	0.0213	0.0231	0.0238	0.0254
		T-statistics	32.29	28.89	23.53	17.14
		N	8201	8221	8251	8331
	Team=1	Mean Value	0.0284	0.0327	0.0341	0.0357
		T-statistics	31.2	28.54	23.59	17.46
		N	5434	5446	5458	5498
	Difference	Mean Value	-0.0071	-0.0096	-0.0103	-0.0102
		T-statistics	-6.5	-7.07	-6.03	-4.14
		N	13635	13667	13709	13829
Remain	Team=0	Mean Value	0.0074	0.0072	0.0061	0.0041
		T-statistics	66.39	54.3	35.47	15.03
		N	208320	208805	209528	211021
	Team=1	Mean Value	0.0091	0.009	0.0076	0.005
		T-statistics	72.45	60.05	39.76	16.8
		N	180672	181025	181649	182909
	Difference	Mean Value	-0.00173	-0.00179	-0.00155	-0.00097
		T-statistics	-10.38	-8.94	-6.05	-2.4
		N	388992	389830	391177	393930
Downgrade	Team=0	Mean Value	-0.0128	-0.0152	-0.0209	-0.03
		T-statistics	-18.88	-18.54	-19.68	-17.66
		N	5468	5485	5505	5537
	Team=1	Mean Value	-0.0139	-0.0158	-0.0189	-0.0282
		T-statistics	-14.15	-13.62	-12.58	-12.49
		N	3027	3033	3047	3071
	Difference	Mean Value	0.00116	0.00067	-0.002	-0.0019
		T-statistics	0.99	0.48	-1.1	-0.66
		N	8495	8518	8552	8608

Table 3: CARs by Recommendation Revision Direction and Seniority (by Reports)

Cumulative abnormal returns are calculated based on Fama-French 3 factor model as explained in section 3.2. All sell-side reports are divided into two subsamples, analyst teams and individual analysts. Panel A reports the result for analyst teams, and Panel B reports the result for individual analysts. Within each sub-sample, reports are sorted by mean seniority and recommendation revision indicator. Seniority measure is based on weighted number of reports issued.

Panel A: CARs by Recommendation Revision Direction and Seniority: Analyst Teams

Revision direction	Seniority. (Reports)	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	1	Mean Value	0.0304	0.0358	0.038	0.0442
		T-statistics	17.23	15.51	12.67	10.84
		N	1599	1604	1608	1624
	2	Mean Value	0.0283	0.0318	0.0337	0.0333
		T-statistics	18.58	16.58	13.84	9.67
		N	1834	1836	1841	1849
	3	Mean Value	0.0271	0.0312	0.0314	0.0311
		T-statistics	18.23	17.38	14.48	9.73
		N	2002	2007	2010	2026
	Difference (1-3)	Mean Value	0.00327	0.00459	0.0066	0.0131
		T-statistics	1.43	1.59	1.82	2.57
Downgrade	1	Mean Value	-0.0149	-0.017	-0.0183	-0.0241
		T-statistics	-8.42	-8.22	-6.82	-5.98
		N	947	951	955	967
	2	Mean Value	-0.01465	-0.0161	-0.0195	-0.0285
		T-statistics	-8.73	-8.11	-7.73	-7.7
		N	1071	1072	1079	1085
	3	Mean Value	-0.0122	-0.01442	-0.01885	-0.03165
		T-statistics	-7.33	-7.26	-7.2	-7.9
		N	1009	1010	1013	1019
	Difference (1-3)	Mean Value	-0.00278	-0.00262	0.000578	0.00756
		T-statistics	-1.15	-0.91	0.15	1.33

Panel B: CARs by Recommendation Revision Direction and Seniority: Individual Analysts

Revision Direction	Seniority. (Reports)	Statistics	AR 3	AR 5	AR 10	AR 30
Upgrade	1	Mean Value	0.0224	0.0244	0.0256	0.0283
		T-statistics	18.17	16.47	13.65	10.4
		N	2443	2451	2458	2477
	2	Mean Value	0.0212	0.0223	0.0224	0.0223
		T-statistics	18.81	16.47	12.96	8.64
		N	2695	2700	2710	2738
	3	Mean Value	0.0205	0.0228	0.0235	0.0259
		T-statistics	18.99	17.14	14.15	10.66
		N	3062	3069	3082	3115
	Difference (1-3)	Mean Value	0.0018	0.00158	0.00208	0.0025
		T-statistics	1.1	0.79	0.83	0.68
Downgrade	1	Mean Value	-0.012	-0.0146	-0.0193	-0.0265
		T-statistics	-9.84	-10.04	-10.19	-9.05
		N	1687	1690	1696	1706
	2	Mean Value	-0.0147	-0.0163	-0.0212	-0.0324
		T-statistics	-12.24	-11.07	-11.03	-10.97
		N	1752	1759	1767	1774
	3	Mean Value	-0.0116	-0.0144	-0.0218	-0.0308
		T-statistics	-10.61	-10.96	-12.76	-10.56
		N	2030	2037	2043	2058
	Difference (1-3)	Mean Value	-0.00043	-0.00016	0.00248	0.00429
		T-statistics	-0.26	-0.08	0.97	1.03

Table 4: Alternative CARs by Revision Direction and Seniority (by Reports)

Cumulative abnormal returns are calculated based on CSI 300 Index as explained in section 3.2. All sell-side reports are divided into two subsamples, analyst teams and individual analysts. Panel A reports the result for analyst teams, and Panel B reports the result for individual analysts. Within each sub-sample, reports are sorted by mean seniority and recommendation revision indicator. Seniority measure is based on weighted number of reports issued.

Panel A: CARs by Recommendation Revision Direction and Seniority: Analyst Teams

Revision direction	Seniority. (Reports)	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	1	Mean Value	0.0334	0.0407	0.0467	0.0698
		T-statistics	18	16.68	14.81	15.71
		N	1619	1624	1630	1641
	2	Mean Value	0.0319	0.0369	0.0433	0.0565
		T-statistics	20.14	18.17	16.83	14.89
		N	1848	1848	1851	1857
	3	Mean Value	0.0281	0.0329	0.0361	0.0468
		T-statistics	18.24	17.49	15.53	13.68
		N	2024	2027	2031	2037
	Difference (1-3)	Mean Value	0.0053	0.00781	0.0107	0.023
		T-statistics	2.22	2.58	2.78	4.17
Downgrade	1	Mean Value	-0.01575	-0.0171	-0.0163	-0.016
		T-statistics	-8.04	-7.42	-5.27	-3.53
		N	959	963	969	977
	2	Mean Value	-0.0143	-0.0144	-0.0144	-0.0186
		T-statistics	-8.19	-6.89	-5.52	-4.61
		N	1078	1078	1083	1088
	3	Mean Value	-0.0131	-0.0139	-0.0132	-0.0203
		T-statistics	-7.39	-6.67	-4.93	-5.12
		N	1014	1015	1017	1022
	Difference (1-3)	Mean Value	-0.00268	-0.00318	-0.0031	0.00433
		T-statistics	-1.02	-1.03	-0.76	0.72

Panel B: CARs by Recommendation Revision Direction and Seniority: Individual Analysts

Revision direction	Seniority. (Reports)	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	1	Mean Value	0.02397	0.027	0.0316	0.044
		T-statistics	18.35	17.02	15.42	14.61
		N	2470	2477	2482	2495
	2	Mean Value	0.0237	0.0262	0.0302	0.0417
		T-statistics	19.98	18.35	16.27	14.73
		N	2723	2727	2736	2751
	3	Mean Value	0.0225	0.0259	0.0303	0.0437
		T-statistics	19.73	18.44	16.92	15.91
		N	3091	3095	3105	3128
	Difference (1-3)	Mean Value	0.00148	0.00113	0.00135	0.000284
		T-statistics	0.86	0.53	0.5	0.07
Downgrade	1	Mean Value	-0.0131	-0.0153	-0.0149	-0.0137
		T-statistics	-9.88	-9.55	-7.11	-4.15
		N	1697	1700	1705	1715
	2	Mean Value	-0.0142	-0.0151	-0.016	-0.0203
		T-statistics	-11.01	-9.6	-7.9	-6.59
		N	1767	1774	1780	1784
	3	Mean Value	-0.0115	-0.0135	-0.0181	-0.0206
		T-statistics	-9.76	-9.56	-9.71	-6.75
		N	2045	2049	2054	2066
	Difference (1-3)	Mean Value	-0.00153	-0.00178	0.00317	0.00681
		T-statistics	-0.86	-0.84	1.13	1.51

Table 5: Absolute Forecast Error and Seniority

This table reports the difference in absolute forecast errors. Absolute forecast error and seniority portfolios are defined and calculated in the way described in section 3.2. Column (1) and (3) reports the result for seniority defined by weighted number of reports. Column (2) and (4) reports the result for seniority defined by number of days as sell-side analysts.

		Team		**Single**	
		(1)	**(2)**	**(3)**	**(4)**
Seniority	**Statistics**	**Reports**	**Exp**	**Reports**	**Exp**
1	Mean Value	0.0287	0.029	0.033	0.0327
	T-statistics	174.19	170.79	221.85	223.39
	N	45483	45492	79017	79013
2	Mean Value	0.0294	0.0291	0.0327	0.033
	T-statistics	176.34	177.22	222.4	222.51
	N	46872	46871	81339	81408
3	Mean Value	0.0307	0.0307	0.0327	0.0328
	T-statistics	169.18	171.32	218.89	217.39
	N	45501	45493	79071	79006
Difference (1-3)	Mean Value	-0.002	-0.00173	0.000351	-0.00008
	T-statistics	-8.14	-7.02	1.66	-0.4

Table 6: Cumulative Abnormal Returns and Seniority (by Reports) within Upgrade Sample

This table shows regression results of cumulative abnormal returns for upgrade subsample and seniority. Abnormal returns are calculated based on FF3 factors or CSI300 Index, for 3,5,10 and 30 trading days. Seniority rankings are calculated based on number of reports issued. Panel A shows the result for team subsample and Panel B shows the result for single subsample. Heteroscedasticity-consistent standard errors, clustered by brokerage firm, are shown in parentheses.

Panel A: Cumulative Abnormal Returns and Seniority (by Reports) within Upgrade Sample: Analyst Team

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Reports)	0.0257*	0.0194	0.0386	0.0468	0.0267**	0.0312*	0.0534**	0.0599*
	(0.0133)	(0.0185)	(0.0251)	(0.0338)	(0.012)	(0.0179)	(0.0239)	(0.0322)
MVE	-0.0341***	-0.0501***	-0.0732***	-0.0930***	-0.0358**	-0.0591***	-0.0834***	-0.121***
	(0.0117)	(0.0166)	(0.0236)	(0.0219)	(0.014)	(0.0188)	(0.0239)	(0.0222)
ROE	0.00278	0.00462	0.0116**	0.0237***	0.00424	0.00748	0.0131**	0.0183**
	(0.00365)	(0.00406)	(0.00555)	(0.00722)	(0.00387)	(0.00458)	(0.00585)	(0.00801)
Analyst Coverage	0.00606	0.0054	0.0123**	0.0129**	0.00788*	0.00819	0.0132**	0.0216***
	(0.004)	(0.00496)	(0.00604)	(0.00647)	(0.00471)	(0.0061)	(0.00654)	(0.00762)
BM	0.00741	0.0104	0.0204*	0.0194	0.0057	0.011	0.0225**	0.0242*
	(0.00605)	(0.00822)	(0.0108)	(0.0148)	(0.00585)	(0.00819)	(0.0103)	(0.0136)
Past Return	0.0130***	0.0176***	0.0226***	0.0483***	0.0122***	0.0182***	0.0255***	0.0605***
	(0.00377)	(0.00472)	(0.00612)	(0.0088)	(0.00401)	(0.0051)	(0.00667)	(0.00899)
Turnover Rate	-0.0109***	-0.0138***	-0.0205***	-0.0264***	-0.0119**	-0.0146***	-0.0225***	-0.0293***
	(0.00398)	(0.00454)	(0.00626)	(0.00954)	(0.0046)	(0.00514)	(0.00715)	(0.00963)
STDDEV	0.0129**	0.0167**	0.0256***	0.0139	0.0145**	0.0202**	0.0294***	0.0259*
	(0.00572)	(0.00725)	(0.00939)	(0.0128)	(0.00659)	(0.0076)	(0.0098)	(0.0138)
Number of Analysts	-0.00343	-0.00588	-0.0071	-0.0102	-0.00286	-0.00245	-0.00681	-0.0114
	(0.00435)	(0.00671)	(0.00715)	(0.0126)	(0.00439)	(0.0065)	(0.00732)	(0.0125)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,528	1,533	1,534	1,544	1,541	1,545	1,549	1,552
R-squared	0.524	0.522	0.562	0.527	0.526	0.521	0.57	0.546

Panel B: Cumulative Abnormal Returns and Seniority (by Reports) within Upgrade Sample: Individual Analysts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Reports)	-0.00188	-0.00359	0.00161	0.00315	0.00192	0.000834	0.00669	0.00445
	(0.00504)	(0.00585)	(0.00859)	(0.0133)	(0.00466)	(0.00551)	(0.00888)	(0.0154)
MVE	-0.0169***	-0.0202***	-0.0226**	-0.0408**	-0.0168***	-0.0191**	-0.0227**	-0.0453***
	(0.00623)	(0.00742)	(0.00964)	(0.0159)	(0.00614)	(0.00739)	(0.00978)	(0.0137)
ROE	0.00323	0.00667***	0.00654**	0.00923**	0.00125	0.00374	0.00483	0.00488
	(0.002)	(0.00242)	(0.0032)	(0.00434)	(0.00188)	(0.00237)	(0.00354)	(0.00518)
Analyst Coverage	0.00169	0.00211	0.000279	-0.00246	0.00216	0.00234	-0.0023	-0.00521
	(0.00216)	(0.003)	(0.00438)	(0.00618)	(0.00205)	(0.0028)	(0.00429)	(0.00576)
BM	0.00426	0.00212	0.00154	0.0131*	0.00800**	0.00567	0.00814*	0.0204***
	(0.00356)	(0.00385)	(0.00436)	(0.00748)	(0.00321)	(0.00377)	(0.00431)	(0.0074)
Past Return	0.00756***	0.00927***	0.0202***	0.0327***	0.00791***	0.00909***	0.0202***	0.0441***
	(0.00222)	(0.00267)	(0.00391)	(0.00573)	(0.00245)	(0.00303)	(0.00424)	(0.00548)
Turnover Rate	-0.00319	-0.00173	-0.00383	-0.00328	-0.00516	-0.00375	-0.00753	-0.00628
	(0.00259)	(0.00301)	(0.00396)	(0.00642)	(0.00333)	(0.00438)	(0.00566)	(0.00804)
STDDEV	0.0129***	0.0147***	0.0130*	0.00422	0.0154***	0.0202***	0.0229***	0.0233*
	(0.0043)	(0.00531)	(0.00755)	(0.0103)	(0.00426)	(0.00549)	(0.00854)	(0.0121)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,008	3,015	3,025	3,045	3,039	3,046	3,056	3,064
R-squared	0.417	0.413	0.393	0.394	0.426	0.418	0.412	0.43

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

Table 7: PMAFE and Seniority

This table shows regression results of PMAFE and seniority. Dependent variable is PMAFE, a measure of relative forecast error as defined in section 3.2. Panel A shows the result for team subsample. Panel B shows the result for single subsample. Heteroscedasticity-consistent standard errors, clustered by brokerage firm, are shown in parentheses.

Panel A: PMAFE and Seniority: Analyst Teams

	(1)	(2)	(3)	(4)	(5)	(6)
Seniority. (Reports)	-0.230***	-0.259***	-0.262***			
	(0.0423)	(0.0384)	(0.0369)			
Seniority. (Exp)				-0.140***	-0.147***	-0.150***
				(0.041)	(0.0391)	(0.0386)
MVE		0.0295*	-0.0149		0.0243	-0.0147
		(0.0167)	(0.0128)		(0.0176)	(0.0128)
ROE		-0.0125**	-0.00864*		-0.0123**	-0.00908*
		(0.00551)	(0.00483)		(0.00551)	(0.00474)
Analyst Coverage		-0.0231***	-0.0149**		-0.0204**	-0.0134*
		(0.00813)	(0.00688)		(0.00834)	(0.00697)
BM		0.00652	0.00159		0.00889	0.00262
		(0.00605)	(0.00593)		(0.00632)	(0.00595)
Past Return		-0.0138*	-0.0011		-0.0135*	-0.00129
		(0.0076)	(0.00716)		(0.00752)	(0.00719)
Turnover Rate		0.0135**	0.00381		0.0133**	0.00443
		(0.00559)	(0.00589)		(0.00559)	(0.00592)
STDDEV		0.00349	-0.00459		0.00376	-0.00515
		(0.00872)	(0.00745)		(0.00844)	(0.00742)
Number of Analysts		-0.0183*	-0.0168*		-0.0129	-0.011
		(0.00946)	(0.0101)		(0.0103)	(0.011)
Constant	0.0680***	0.126***	0.125***	0.0115	0.0443	0.0421
	(0.023)	(0.0287)	(0.0289)	(0.0227)	(0.0322)	(0.0332)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes	Yes		Yes	Yes
Year FE			Yes			Yes
Observations	86,642	83,918	83,918	86,642	83,918	83,918
R-squared	0.002	0.028	0.03	0.001	0.026	0.028

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

Panel B: PMAFE and Seniority: Individual Analysts

	(1)	(2)	(3)	(4)	(5)	(6)
Seniority. (Reports)	-0.134***	-0.141***	-0.140***			
	(0.0211)	(0.0221)	(0.0223)			
Seniority. (Exp)				-0.0720***	-0.0765***	-0.0751***
				(0.017)	(0.0177)	(0.018)
MVE		-0.000372	-0.00174		-0.00132	-0.000723
		(0.0153)	(0.012)		(0.0152)	(0.0121)
ROE		-0.00197	0.00007		-0.00179	0.00007
		(0.00529)	(0.00533)		(0.00536)	(0.00537)
Analyst Coverage		-0.00759	-0.00725		-0.00649	-0.00632
		(0.00608)	(0.00509)		(0.00613)	(0.00514)
BM		-0.0149**	-0.00508		-0.0152**	-0.00546
		(0.00716)	(0.00678)		(0.00728)	(0.00683)
Past Return		0.00828	-0.00165		0.00936	-0.00106
		(0.00651)	(0.00672)		(0.00652)	(0.00679)
Turnover Rate		-0.00107	-0.00148		-0.00121	-0.00136
		(0.00491)	(0.00469)		(0.0049)	(0.00469)
STDDEV		-0.00691	0.00203		-0.00628	0.00179
		(0.00594)	(0.00629)		(0.00592)	(0.00633)
Constant	0.0991***	0.104***	0.104***	0.0535***	0.0563***	0.0556***
	(0.0126)	(0.0129)	(0.013)	(0.0112)	(0.0113)	(0.0114)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes	Yes		Yes	Yes
Year FE			Yes			Yes
Observations	133,437	128,760	128,760	133,437	128,760	128,760
R-squared	0.002	0.011	0.012	0.001	0.01	0.011

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

Table 8: CARs by Recommendation Revision Direction and Seniority (by Experience)

Cumulative abnormal returns are calculated based on Fama-French 3 factor model as explained in section 3.2. All sell-side reports are divided into two subsamples, analyst teams and individual analysts. Panel A reports the result for analyst teams, and Panel B reports the result for individual analysts. Within each sub-sample, reports are sorted by mean seniority and recommendation revision indicator. Seniority measure is based on number of days as sell-side analysts.

Panel A: CARs by Recommendation Revision Direction and Seniority (by Experience): Teams

Revision Direction	Seniority	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	1	Mean Value	0.0296	0.0351	0.0381	0.041
		T-statistics	17.74	16.12	13.53	10.39
		N	1688	1690	1697	1710
	2	Mean Value	0.0278	0.0306	0.0319	0.0347
		T-statistics	18.14	15.92	13.19	10.26
		N	1826	1833	1836	1849
	3	Mean Value	0.028	0.0327	0.0328	0.032
		T-statistics	18.16	17.39	14.17	9.6
		N	1921	1924	1926	1940
	Difference (1-3)	Mean Value	0.00181	0.00247	0.0053	0.00904
		T-statistics	0.8	0.86	1.47	1.76
Downgrade	1	Mean Value	-0.0157	-0.018	-0.021	-0.0303
		T-statistics	-9.57	-9.14	-8.37	-7.67
		N	1012	1014	1020	1030
	2	Mean Value	-0.0141	-0.016	-0.0185	-0.0263
		T-statistics	-8.09	-7.87	-7.09	-7.01
		N	1049	1052	1054	1062
	3	Mean Value	-0.0118	-0.0134	-0.0171	-0.028
		T-statistics	-6.89	-6.59	-6.37	-6.93
		N	966	967	973	979
	Difference (1-3)	Mean Value	-0.00392	-0.00461	-0.00388	-0.00226
		T-statistics	-1.65	-1.63	-1.06	-0.4

Panel B: CARs by Recommendation Revision Direction and Seniority (by Experience): Individual Analysts

Revision Direction	Seniority	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	1	Mean Value	0.0208	0.0227	0.0233	0.0264
		T-statistics	17.83	16.1	12.95	9.98
		N	2590	2596	2600	2621
	2	Mean Value	0.0207	0.0223	0.0228	0.0225
		T-statistics	19.24	17.06	13.81	8.89
		N	2764	2769	2779	2805
	3	Mean Value	0.0222	0.0243	0.0251	0.0275
		T-statistics	18.93	16.95	14.02	10.8
		N	2846	2855	2871	2904
	Difference (1-3)	Mean Value	-0.0014	-0.00156	-0.00184	-0.00118
		T-statistics	-0.84	-0.77	-0.72	-0.32
Downgrade	1	Mean Value	-0.013	-0.0159	-0.0204	-0.0303
		T-statistics	-10.43	-10.66	-10.47	-10.21
		N	1659	1663	1670	1681
	2	Mean Value	-0.0132	-0.0158	-0.0224	-0.0319
		T-statistics	-11.68	-11.69	-12.76	-11.6
		N	1937	1945	1952	1959
	3	Mean Value	-0.012	-0.0136	-0.0195	-0.0277
		T-statistics	-10.53	-9.74	-10.79	-8.96
		N	1873	1878	1884	1898
	Difference (1-3)	Mean Value	-0.00097	-0.00234	-0.00086	-0.00259
		T-statistics	-0.58	-1.14	-0.32	-0.6

Table 9: Alternative CARs by Recommendation Revision Direction and Seniority (by Experience)

Cumulative abnormal returns are calculated based on CSI 300 Index as explained in section 3.2. All sell-side reports are divided into two subsamples, analyst teams and individual analysts. Panel A reports the result for analyst teams, and Panel B reports the result for individual analysts. Within each sub-sample, reports are sorted by mean seniority and recommendation revision indicator. Seniority measure is based on number of days as sell-side analysts.

Panel A: CARs by Recommendation Revision Direction and Seniority: Teams

Revision Direction	Seniority	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	1	Mean Value	0.0331	0.0402	0.0469	0.0671
		T-statistics	18.88	17.54	16.01	15.9
		N	1705	1707	1713	1721
	2	Mean Value	0.0302	0.0348	0.0409	0.0579
		T-statistics	18.68	16.9	15.58	15.24
		N	1848	1851	1854	1861
	3	Mean Value	0.0295	0.0349	0.0377	0.047
		T-statistics	18.74	17.84	15.48	13.11
		N	1938	1941	1945	1953
	Difference (1-3)	Mean Value	0.0036	0.00532	0.00923	0.0201
		T-statistics	1.53	1.77	2.44	3.65
Downgrade	1	Mean Value	-0.016	-0.0171	-0.0178	-0.021
		T-statistics	-9.29	-8.43	-6.78	-5.12
		N	1018	1020	1025	1035
	2	Mean Value	-0.0148	-0.0155	-0.0145	-0.0157
		T-statistics	-7.89	-6.91	-4.99	-3.68
		N	1064	1066	1069	1071
	3	Mean Value	-0.012	-0.0124	-0.0111	-0.0184
		T-statistics	-6.52	-5.73	-4.04	-4.46
		N	969	970	975	981
	Difference (1-3)	Mean Value	-0.00407	-0.00469	-0.00667	-0.00252
		T-statistics	-1.61	-1.58	-1.75	-0.43

Panel B: CARs by Recommendation Revision Direction and Seniority: Individual Analysts

Revision Direction	Seniority	Statistics	AR_3	AR_5	AR_10	AR_30
Upgrade	1	Mean Value	0.0232	0.0265	0.0311	0.0424
		T-statistics	18.87	17.59	15.76	14.61
		N	2612	2616	2619	2637
	2	Mean Value	0.0229	0.0257	0.0297	0.0414
		T-statistics	19.89	18.52	16.53	14.56
		N	2797	2801	2811	2824
	3	Mean Value	0.0237	0.0266	0.031	0.0455
		T-statistics	19.34	17.76	16.37	16.07
		N	2875	2882	2893	2913
	Difference (1-3)	Mean Value	-0.00046	-0.00015	0.000105	-0.00309
		T-statistics	-0.26	-0.07	0.04	-0.76
Downgrade	1	Mean Value	-0.0135	-0.0154	-0.016	-0.0205
		T-statistics	-10.07	-9.31	-7.38	-6.13
		N	1671	1675	1682	1691
	2	Mean Value	-0.013	-0.0152	-0.0183	-0.0197
		T-statistics	-10.57	-10.42	-9.81	-6.79
		N	1950	1957	1962	1970
	3	Mean Value	-0.0121	-0.0131	-0.0147	-0.015
		T-statistics	-9.95	-8.94	-7.61	-4.7
		N	1888	1891	1895	1904
	Difference (1-3)	Mean Value	-0.00144	-0.00228	-0.00125	-0.00551
		T-statistics	-0.8	-1.04	-0.43	-1.19

Table 10: CARs and Seniority (by Experience) within Upgrade Sample

This table shows regression results of cumulative abnormal returns for upgrade subsample and seniority. Cumulative abnormal returns are calculated based on FF3 factors or CSI300 Index, for 3,5,10 and 30 trading days. Seniority rankings are calculated based on number of days as sell-side analysts. Panel A shows the result for team subsample and Panel B shows the result for single subsample. Heteroscedasticity-consistent standard errors, clustered by industry, are shown in parentheses.

Panel A: CARs and Seniority (by Experience) within Upgrade Sample: Teams

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Exp)	0.0275**	0.0255	0.0407*	0.0513	0.0305***	0.0367**	0.0566***	0.0714**
	(0.0121)	(0.0157)	(0.0224)	(0.0346)	(0.0107)	(0.0163)	(0.0199)	(0.0341)
MVE	-0.0345***	-0.0503***	-0.0739***	-0.0938***	-0.0361**	-0.0595***	-0.0844***	-0.122***
	(0.0118)	(0.0167)	(0.0238)	(0.0223)	(0.0142)	(0.0189)	(0.0242)	(0.0224)
ROE	0.00301	0.00488	0.0120**	0.0242***	0.00451	0.00783*	0.0136**	0.0190**
	(0.00356)	(0.00399)	(0.00551)	(0.00727)	(0.00381)	(0.00458)	(0.00584)	(0.00803)
Analyst Coverage	0.00607	0.00544	0.0123**	0.0129**	0.00789*	0.00822	0.0132**	0.0216***
	(0.00399)	(0.00493)	(0.006)	(0.00647)	(0.00472)	(0.0061)	(0.0065)	(0.00768)
BM	0.00743	0.0104	0.0203*	0.0193	0.00563	0.0109	0.0224**	0.0240*
	(0.00601)	(0.00818)	(0.0108)	(0.0147)	(0.00583)	(0.00812)	(0.0102)	(0.0136)
Past Return	0.0130***	0.0175***	0.0227***	0.0483***	0.0122***	0.0182***	0.0256***	0.0605***
	(0.00381)	(0.00475)	(0.00618)	(0.00886)	(0.00406)	(0.00516)	(0.00677)	(0.00904)
Turnover Rate	-0.0110***	-0.0138***	-0.0206***	-0.0265***	-0.0119**	-0.0146***	-0.0226***	-0.0293***
	(0.004)	(0.00452)	(0.00625)	(0.00958)	(0.00462)	(0.00512)	(0.00713)	(0.00964)
STDDEV	0.0131**	0.0168**	0.0260***	0.0144	0.0147**	0.0204***	0.0300***	0.0265*
	(0.00564)	(0.00713)	(0.00934)	(0.0129)	(0.00652)	(0.00747)	(0.0098)	(0.0138)
Number of Analysts	-0.00384	-0.00601	-0.00772	-0.0109	-0.00316	-0.00279	-0.0077	-0.0121
	(0.00428)	(0.00658)	(0.00687)	(0.0124)	(0.00436)	(0.00635)	(0.00695)	(0.0123)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,528	1,533	1,534	1,544	1,541	1,545	1,549	1,552
R-squared	0.524	0.523	0.562	0.528	0.527	0.522	0.57	0.546

Panel B: CARs and Seniority (by Experience) within Upgrade Sample: Individual Analysts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Exp)	-0.00177	-0.00244	-0.00135	0.00864	0.00282	0.00186	0.00499	0.00848
	(0.00446)	(0.0052)	(0.00747)	(0.0116)	(0.00447)	(0.00567)	(0.00827)	(0.0137)
MVE	-0.0169***	-0.0201***	-0.0226**	-0.0409**	-0.0169***	-0.0191**	-0.0229**	-0.0454***
	(0.00624)	(0.00739)	(0.00963)	(0.0156)	(0.00614)	(0.00737)	(0.00972)	(0.0135)
ROE	0.00321	0.00667***	0.00649**	0.00938**	0.00129	0.00377	0.00485	0.00501
	(0.00202)	(0.00243)	(0.00321)	(0.00432)	(0.0019)	(0.00239)	(0.00356)	(0.00521)
Analyst Coverage	0.00169	0.00212	0.000279	-0.00247	0.00215	0.00234	-0.00231	-0.00523
	(0.00216)	(0.00301)	(0.00437)	(0.00622)	(0.00205)	(0.0028)	(0.00428)	(0.00578)
BM	0.00426	0.0021	0.00158	0.0130*	0.00798**	0.00565	0.00815*	0.0204***
	(0.00355)	(0.00384)	(0.00436)	(0.0075)	(0.00321)	(0.00376)	(0.00432)	(0.0074)
Past Return	0.00756***	0.00927***	0.0201***	0.0329***	0.00793***	0.00911***	0.0202***	0.0442***
	(0.00221)	(0.00266)	(0.00389)	(0.00573)	(0.00244)	(0.00301)	(0.00422)	(0.00547)
Turnover Rate	-0.00318	-0.0017	-0.00389	-0.00319	-0.00515	-0.00374	-0.00756	-0.00621
	(0.00259)	(0.00301)	(0.00397)	(0.00643)	(0.00333)	(0.00438)	(0.00567)	(0.00805)
STDDEV	0.0129***	0.0147***	0.0130*	0.00423	0.0154***	0.0202***	0.0230***	0.0233*
	(0.00429)	(0.0053)	(0.00754)	(0.0103)	(0.00426)	(0.00548)	(0.00852)	(0.012)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,008	3,015	3,025	3,045	3,039	3,046	3,056	3,064
R-squared	0.417	0.413	0.393	0.395	0.426	0.418	0.412	0.431

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

Table 11: Team changes and PMAFE

Dependent variable is PMAFE as explained in section 3.2. B0_A1 and B1_A0 are dummy variables as explained in section 6.1. B0_A1 indicates the situation of team-change such that, an analyst team without any senior analysts joined by at least one senior analyst during the team-change. B1_A0 indicates the situation of team-change such that, an analyst team with at least one senior analyst before the team-change lost all the senior analysts after the team-change. Heteroscedasticity-consistent standard errors, clustered by brokerage firm, are shown in parentheses.

	(1)	(2)	(3)	(4)
B0_A1	-0.0460**	-0.0498***	-0.0585***	-0.0585***
	(0.0176)	(0.0182)	(0.0175)	(0.0175)
B1_A0	0.0231	0.0225	0.0202	0.0202
	(0.0217)	(0.0265)	(0.026)	(0.026)
MVE. (Fenddt)		0.0325	0.215***	0.215***
		(0.0321)	(0.0321)	(0.0321)
ROE		-0.0150*	-0.0365***	-0.0365***
		(0.00853)	(0.00831)	(0.00831)
Analyst Coverage		-0.0228**	-0.0637***	-0.0637***
		(0.0105)	(0.0144)	(0.0144)
BM. (Fenddt)		-0.00501	-0.0319*	-0.0319*
		(0.0166)	(0.0188)	(0.0188)
Past Return		-0.00891	0.00757	0.00757
		(0.0132)	(0.0116)	(0.0116)
Turnover		0.0149	0.0429***	0.0429***
		(0.00998)	(0.0115)	(0.0115)
STDDEV		-0.0109	-0.0356**	-0.0356**
		(0.0119)	(0.0155)	(0.0155)
Constant	-0.153***	-0.154***	-0.155***	-0.155***
	(0.0127)	(0.0121)	(0.0119)	(0.0119)
Clustered by Broker	Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes
Year FE			Yes	Yes
Industry FE				Yes
Observations	18,537	17,787	17,787	17,787
R-squared	0	0.103	0.119	0.119

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

Table 12: Team changes, PMAFE, and Senior Analysts

Dependent variable is PMAFE as explained in section 3.2. Sum senior is the total number of senior analysts in the team. Heteroscedasticity-consistent standard errors, clustered by brokerage firm, are shown in parentheses.

	(1)	(2)	(3)
Sum_Senior	-0.0513***	-0.0637***	-0.0634***
	(0.0101)	(0.011)	(0.0114)
MVE		0.0337	-0.036
		(0.0307)	(0.031)
ROE		-0.0145*	-0.0114
		(0.00852)	(0.00806)
Analyst coverage		-0.0250**	-0.0213
		(0.0108)	(0.014)
BM		-0.00586	-0.00937
		(0.0167)	(0.0206)
Past Return		-0.00837	0.0301**
		(0.0133)	(0.0127)
Turnover Rate		0.0149	0.0127
		(0.0101)	(0.0118)
STDDEV		-0.0113	-0.0209
		(0.0117)	(0.0169)
Number Analysts		0.0243**	0.0278**
		(0.0104)	(0.0106)
Constant	-0.101***	-0.149***	-0.156***
	(0.0147)	(0.0313)	(0.0329)
Clustered by Broker	Yes	Yes	Yes
Firm FE		Yes	Yes
Year FE			Yes
Observations	18,537	17,787	17,786
R-squared	0.002	0.105	0.108

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

Table 13: Team changes, PMAFE, and B0*Sum_Senior

Dependent variable is PMAFE as explained in section 3.2. Sum senior is the total number of senior analysts in the team after team-change. B0 equals to one if no senior analysts before team change. B0*Sum senior is the interaction term. Heteroscedasticity-consistent standard errors, clustered by brokerage firm, are shown in parentheses.

	(1)	(2)	(3)
B0*Sum_Senior	-0.107***	-0.0944***	-0.0999***
	(0.0252)	(0.0238)	(0.0228)
B0	0.0874***	0.0762***	0.0799***
	(0.03)	(0.0281)	(0.0254)
Sum Senior	-0.0312***	-0.0448***	-0.0436***
	(0.0105)	(0.0126)	(0.0131)
MVE		0.0338	-0.0349
		(0.0308)	(0.0313)
ROE		-0.0148*	-0.0119
		(0.0085)	(0.00808)
Analyst coverage		-0.0248**	-0.0219
		(0.0107)	(0.0141)
BM		-0.00593	-0.00936
		(0.0165)	(0.0204)
Past Return		-0.00814	0.0305**
		(0.0133)	(0.0127)
Turnover Rate		0.0139	0.0122
		(0.0101)	(0.0119)
STDDEV		-0.0118	-0.0211
		(0.0117)	(0.0169)
Number analysts		0.0191*	0.0224**
		(0.0102)	(0.0103)
Constant	-0.126***	-0.159***	-0.167***
	(0.0202)	(0.0343)	(0.0357)
Clustered by Broker	Yes	Yes	Yes
Firm FE		Yes	Yes
Year FE			Yes
Observations	18,537	17,787	17,786
R-squared	0.003	0.106	0.109

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

A. Internet Appendix

Table A.1: CARs and Seniority (by Reports) within Downgrade Sample

This table shows regression results of cumulative abnormal returns for downgrade subsample and seniority. Abnormal returns are calculated based on FF3 factors and CSI300 Index. Seniority rankings are calculated based on number of reports issued. Panel A is the result for team subsample and Panel B is the result for single subsample.

Panel A: CARs and Seniority (by Reports) within Downgrade Sample: Teams

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Reports)	-0.0111	-0.00551	-0.0102	0.00136	-0.0127	-0.0109	-0.0223	-0.0122
	(0.0134)	(0.0136)	(0.0185)	(0.0295)	(0.0154)	(0.0148)	(0.0214)	(0.0302)
MVE	0.0109	0.0194	0.0288*	0.0169	0.0104	0.0188	0.0221	-0.00321
	(0.00942)	(0.0123)	(0.015)	(0.0199)	(0.0115)	(0.0141)	(0.0156)	(0.0196)
ROE	0.0001	-0.000203	-0.00149	0.000696	-0.00167	-0.0022	-0.00261	0.00326
	(0.00252)	(0.00265)	(0.00254)	(0.00654)	(0.00272)	(0.00306)	(0.00289)	(0.00704)
Analyst Coverage	-0.00413	-0.00760*	-0.0133**	-0.00337	-0.00555	-0.00631	-0.00913	0.00167
	(0.00348)	(0.00424)	(0.00649)	(0.00884)	(0.00372)	(0.00446)	(0.0071)	(0.00965)
BM	-0.00828*	-0.0118*	-0.0160*	-0.0131	-0.00341	-0.00666	-0.00894	0.00411
	(0.00456)	(0.00611)	(0.00854)	(0.0171)	(0.00531)	(0.00649)	(0.00841)	(0.0154)
Past Return	0.00336	0.00112	0.00683	0.0299***	0.00488	0.00432	0.0113*	0.0339***
	(0.00331)	(0.00393)	(0.0064)	(0.00988)	(0.00396)	(0.00482)	(0.0067)	(0.00983)
Turnover Rate	0.00473	0.00747	0.0153**	0.0128	0.00486	0.00505	0.0119*	0.00671
	(0.00455)	(0.00509)	(0.00659)	(0.0103)	(0.00486)	(0.00557)	(0.00674)	(0.00902)
STDDEV	-0.0101*	-0.0149**	-0.0217**	-0.0266	-0.0105*	-0.0141*	-0.0165*	-0.00362
	(0.00535)	(0.00636)	(0.0094)	(0.0166)	(0.0055)	(0.00728)	(0.00968)	(0.0155)
Number of Analysts	0.00297	0.00297	-0.00212	0.0104	0.00375	0.00671	-0.00289	0.0041
	(0.00516)	(0.00558)	(0.00567)	(0.0105)	(0.00529)	(0.00632)	(0.00578)	(0.01)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	960	962	964	967	965	967	969	973
R-squared	0.521	0.533	0.535	0.525	0.525	0.528	0.522	0.549

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

Panel B: CARs and Seniority (by Reports) within Downgrade Sample: Individual Analysts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Reports)	-0.000609	0.00195	0.00732	0.00518	-0.000153	0.00225	0.00876	0.00582
	(0.00515)	(0.00551)	(0.00762)	(0.0134)	(0.00537)	(0.0064)	(0.009)	(0.0133)
MVE	0.000785	0.00285	0.0141	0.0139	0.0015	0.00542	0.0139	0.0021
	(0.00628)	(0.0084)	(0.0107)	(0.0126)	(0.00682)	(0.00844)	(0.0111)	(0.0141)
ROE	0.000158	0.00184	-0.00107	0.00101	-0.00067	-0.00003	-0.00394	-0.00173
	(0.00165)	(0.00207)	(0.00314)	(0.00461)	(0.00199)	(0.00256)	(0.00369)	(0.00448)
Analyst Coverage	0.000279	0.00005	-0.000421	0.00007	0.00003	-0.000157	0.00157	0.00384
	(0.00258)	(0.0029)	(0.00389)	(0.00647)	(0.00262)	(0.0029)	(0.00408)	(0.00656)
BM	-0.00414	-0.00525	-0.00971	-0.00231	-0.00334	-0.00215	-0.00753	0.00114
	(0.00422)	(0.00662)	(0.00819)	(0.0105)	(0.00427)	(0.0063)	(0.00794)	(0.0106)
Past Return	0.00891***	0.0104***	0.0142***	0.0319***	0.0102***	0.0108***	0.0171***	0.0418***
	(0.00231)	(0.00283)	(0.0038)	(0.00688)	(0.00238)	(0.00311)	(0.00414)	(0.00734)
Turnover Rate	-0.00163	0.00156	0.00136	0.00998	-0.00135	0.0018	0.00156	0.0159**
	(0.00299)	(0.00341)	(0.00424)	(0.00718)	(0.00324)	(0.00387)	(0.00534)	(0.00683)
STDDEV	-0.00708**	-0.00781*	-0.00637	-0.0213*	-0.0107**	-0.0122**	-0.0136	-0.0225*
	(0.0035)	(0.00451)	(0.00708)	(0.0121)	(0.00424)	(0.0056)	(0.00857)	(0.0116)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,348	2,358	2,366	2,373	2,366	2,374	2,379	2,383
R-squared	0.405	0.415	0.442	0.42	0.419	0.419	0.437	0.431

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

Table A.2: CARs and Seniority (by Experience) within Downgrade Sample

This table shows regression results of Abnormal return for downgrade subsample and seniority. Abnormal returns are calculated based on FF3 factors and CSI300 Index. Seniority rankings are calculated based on days of experience. Panel A is the result for team subsample and Panel B is the result for single subsample.

Panel A: CARs and Seniority (by Experience) within Downgrade Sample: Teams

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Exp)	-0.00783	-0.00236	-0.0135	0.0094	-0.00515	0.000534	-0.0165	-0.0123
	(0.0106)	(0.0107)	(0.0178)	(0.0288)	(0.0125)	(0.0119)	(0.0193)	(0.0319)
MVE	0.0109	0.0193	0.0289*	0.0168	0.0103	0.0187	0.0221	-0.00315
	(0.00943)	(0.0123)	(0.015)	(0.0201)	(0.0116)	(0.0143)	(0.0156)	(0.0195)
ROE	0.00007	-0.000213	-0.00153	0.000723	-0.00169	-0.0022	-0.00266	0.00322
	(0.00253)	(0.00266)	(0.00255)	(0.00656)	(0.00272)	(0.00307)	(0.00291)	(0.00709)
Analyst Coverage	-0.00408	-0.00756*	-0.0133**	-0.00331	-0.00546	-0.00619	-0.00903	0.00169
	(0.00349)	(0.00427)	(0.00651)	(0.00887)	(0.00374)	(0.00453)	(0.00716)	(0.00968)
BM	-0.00831*	-0.0118*	-0.0161*	-0.0129	-0.00337	-0.00653	-0.00901	0.00398
	(0.00453)	(0.00608)	(0.00861)	(0.0171)	(0.00526)	(0.00645)	(0.00846)	(0.0155)
Past Return	0.0035	0.00117	0.00703	0.0297***	0.00499	0.00435	0.0115*	0.0341***
	(0.00338)	(0.00397)	(0.00645)	(0.00998)	(0.00402)	(0.00489)	(0.00677)	(0.00983)
Turnover Rate	0.00458	0.00739	0.0152**	0.0128	0.00467	0.00486	0.0116*	0.00654
	(0.00455)	(0.00508)	(0.00661)	(0.0104)	(0.0048)	(0.00554)	(0.00675)	(0.00914)
STDDEV	-0.00989*	-0.0148**	-0.0215**	-0.0266	-0.0102*	-0.0138*	-0.016	-0.00333
	(0.00525)	(0.00632)	(0.00937)	(0.0167)	(0.0054)	(0.00727)	(0.00965)	(0.0156)
Number of Analysts	0.00306	0.00304	-0.0021	0.0105	0.00389	0.00688	-0.00272	0.00415
	(0.00512)	(0.00556)	(0.00563)	(0.0106)	(0.00523)	(0.00628)	(0.00572)	(0.00994)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	960	962	964	967	965	967	969	973
R-squared	0.521	0.533	0.535	0.525	0.525	0.528	0.522	0.549

Panel B: CARs and Seniority (by Experience) within Downgrade Sample: Individual Analysts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	FF3_3	FF3_5	FF3_10	FF3_30	Index_3	Index_5	Index_10	Index_30
Seniority. (Experience)	-0.00351	-0.00374	0.000444	-0.007	-0.00197	-0.00103	0.00177	-0.00637
	(0.00483)	(0.00524)	(0.00801)	(0.0128)	(0.00511)	(0.00609)	(0.00916)	(0.0131)
MVE	0.000829	0.0029	0.0141	0.014	0.00153	0.00544	0.0139	0.0022
	(0.00626)	(0.00837)	(0.0107)	(0.0125)	(0.00682)	(0.00842)	(0.0111)	(0.014)
ROE	0.000169	0.00186	-0.00106	0.00104	-0.000664	-0.00002	-0.00394	-0.0017
	(0.00165)	(0.00208)	(0.00314)	(0.00463)	(0.00199)	(0.00256)	(0.00369)	(0.00449)
Analyst Coverage	0.000266	-0.00009	-0.000496	-0.00002	0.00002	-0.000188	0.00148	0.00374
	(0.00258)	(0.0029)	(0.00388)	(0.00645)	(0.00262)	(0.0029)	(0.00409)	(0.00655)
BM	-0.00408	-0.00511	-0.00951	-0.00202	-0.0033	-0.00206	-0.00733	0.00142
	(0.0042)	(0.00658)	(0.00814)	(0.0104)	(0.00425)	(0.00627)	(0.00789)	(0.0106)
Past Return	0.00887***	0.0103***	0.0140***	0.0316***	0.0102***	0.0107***	0.0169***	0.0415***
	(0.0023)	(0.00284)	(0.00378)	(0.00687)	(0.00238)	(0.00313)	(0.00413)	(0.00732)
Turnover Rate	-0.00164	0.00156	0.00138	0.00997	-0.00135	0.00179	0.00157	0.0159**
	(0.00298)	(0.00341)	(0.00425)	(0.00718)	(0.00324)	(0.00387)	(0.00535)	(0.00682)
STDDEV	-0.00710**	-0.00782*	-0.00637	-0.0213*	-0.0107**	-0.0122**	-0.0136	-0.0225*
	(0.0035)	(0.00451)	(0.00708)	(0.0121)	(0.00425)	(0.00561)	(0.00859)	(0.0115)
Clustered by Broker	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,348	2,358	2,366	2,373	2,366	2,374	2,379	2,383
R-squared	0.405	0.415	0.441	0.42	0.419	0.419	0.437	0.431

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

Chapter 4. Synchronicity and price informativeness: Evidence from analysts' recommendation revisions

4.1. Introduction

In the first chapter of my thesis, I use synchronicity (either correlation coefficient between individual stock return and market return, or R-squared of regression) as proxy for firm-specific information. Roll (1988) was among the first to study the role of R-squared of regression, or synchronicity, in comprehending the information environment of stock market. Synchronicity measures the relative amount of firm-specific information that is incorporated into stock prices, thus lower synchronicity indicates higher level of firm-specific information. Research based on similar assumptions includes Morck, Yeung, and Yu (2000), Piotroski and Roulstone (2004), Durnev, Morck, and Yeung (2005), Chan and Hameed (2006), Gul, Kim, and Qiu (2010), Crawford, Roulstone, and So (2012) just to name a few. Based on this assumption, lower synchronicity is usually considered as a good attribute of firms, indicating better information environment and stock price informativeness. However, this might not be the only way to interpret the role of synchronicity. Another strand of literature suggests that lower synchronicity indicates lower level of firm-specific information, therefore is associated with worse information environment. For instance, Dasgupta, Gan, and Gao (2010) find that more transparent environment actually leads to higher return synchronicity, whereas Chan and Chan (2014) show synchronicity is positively associated with stock information environment by studying the seasoned equity offering discounts. Devos, Hao, Prevost, and Wongchoti (2015) suggest that lower synchronicity is associated with noisier and less informative environment by studying the abnormal trading volume and volatility associated with analyst recommendation revisions. Some literature further argue that synchronicity is not a good proxy of information environment at all. For instance, Xing and Anderson (2011) suggest that relationship between synchronicity and firm-specific information is not linear but U-shaped instead, while Skaife, Gassen, and Veenman (2014) argue that synchronicity is not a useful and accurate measure to proxy for information environment in international market. In summary, existing literature is somewhat ambiguous on relationship between synchronicity and information environment.

In this research, I study the relation between synchronicity and level of firm-specific information incorporated into stock prices using data collected from Chinese financial markets with recommendation revisions issued by sell-side analysts between 2010 and 2020. Recommendation and recommendation revisions issued by sell-side analysts are widely considered as providing significant amount of firm-specific information to the market. For instance, Womack (1996) and Barber, Lehavy, McNichols, and Trueman (2001) provide some early evidence that recommendations issued by sell-side analysts are associated with abnormal returns and contain information, whereas Ivkovi´c and Jegadeesh (2004) study the recommendation revisions and examines the association between characteristics of different types of recommendation revisions and their information content. Although some literature focus on pure recommendations (see, for instance, Barbera, Lehavyb, McNicholsc, and Trueman, 2006), in this research I focus on recommendation revisions. Focusing on recommendation revisions instead of pure recommendations would mitigate the optimistic bias towards favorable ratings issued by analysts as discussed in Jegadeesh, Kim, Krische, and Lee (2004) and Jegadeesh and Kim (2006). Sell-side analysts provide firm-specific information to their buy-side institutional clients when they issue recommendation revisions. They usually communicate with their clients by engaging in private phone calls and one-to-one with buy-side analysts and portfolio managers as Maber, Groysberg, and

Healy (2021) suggest.

Given that sell-side analysts provide firm-specific information during recommendation revisions, we should expect to see a decrease in synchronicity after a recommendation revision if synchronicity is indeed negatively associated with level of firm-specific information and information environment. To test this theory, I calculate the synchronicity values (both R-squared and correlation coefficient) before and after each recommendation revision take place and examine their changes with regression tests. Synchronicity before and after recommendation revisions are both calculated using daily returns of 45 trading days, which approximately represents 2 calendar months. To ease the concern that changes in synchronicity are mechanically driven by the abnormal returns around recommendation revision announcement dates, I exclude the daily returns of 5 trading days both before and after each recommendation revision. After controlling for a series of relevant variables that could potentially affect synchronicity, I find that 45 trading days synchronicity tend to significantly decrease after recommendation revisions. Recommendation revision is associated with lower synchronicity afterwards. This indicates lower synchronicity is indeed associated with more firm-specific information incorporated into stock prices and better information environment, supporting the underlying theory of Roll (1988), Morck et al. (2000), Piotroski and Roulstone (2004) and many others.

As for robustness check, I first re-calculate synchronicity values before and after each recommendation revision without excluding daily returns for 5 trading days before and after revision announcement and run the same regression test. The result, however, is still negative and statistically significant. Then to further examine the robustness of my main result, I calculate another measure as proxy for synchronicity besides R-squared, namely correlation coefficient, while using the same number of trading days before and after revisions, as seen in Huang, Huang, and Lin (2019) and Li, Liu, and Pursiainen (2022). Correlation coefficient between individual stock returns and market returns decreases significantly after recommendation revisions, in line with results suggested in main analysis. Next, instead of using 45 trading days before and after recommendation revisions to calculate synchronicity, I calculate synchronicity values based on 30 trading days and 60 trading days before and after recommendation revisions accordingly as alternative measures. For both measures, synchronicity significantly decrease after announcement days. This is in line with the assumption that lower synchronicity is associate with higher level of firm-specific information content and better stock price informativeness.

The natural follow up question to discuss after showing the negative association between stock return synchronicity and level of the firm-specific information content incorporated into stock prices is that, how these changes of synchronicity take place before and after recommendation revisions on daily basis. I therefore develop a new measure to proxy the changes of synchronicity on daily basis and name it "moving synchronicity". As Figure 1 shows, the firm-specific information content starts to increase as early as 15 trading days before recommendation revisions take place, as evidenced by the decreasing R-squared values. This evidence suggests possible leak of valuable information from sell-side analysts to their buy-side institutional clients way ahead of actual revision announcements. This result is in line with the theory and empirical findings of Christophe, Ferri, and Hsieh (2010), Niehaus and Zhang (2010), and Madura and Premti (2014) that sell-side analysts are incentivized to leak information prior to the public announcement of recommendations. Figure 1 also indicates that changes of information content provided by recommendation revisions lasts for around 30 trading days after actual announcements and slowly fade away afterwards.

Next, I examine whether seniority of analyst (teams) would affect the level of synchronicity changes after recommendation revisions using cross-sectional analysis. Seniority is defined in the same method as in the second chapter of this thesis. At the beginning of each quarter, I rank all active sell-side analysts based on the number of days they've been working in the sell-side industry and assign a percentage score to each of them accordingly. Seniority of each analyst team is then calculated by directly taking the average of each team members' seniority score. Seniority scores for analysts and analyst teams are only valid for one quarter and are updated on a quarterly basis. Recommendation revisions issued by analyst teams within the upper half of seniority scores are considered as issued by senior analysts or analyst teams. Recommendation revisions issued by senior analysts or analyst teams experience even larger decreases in synchronicity, suggesting that these recommendation revisions contain more firm-specific information and could further improve information environment comparing with revisions issued by their non-senior counterparts. This result is in line with the empirical findings of chapter 3 of this thesis that sell-side reports and recommendations issued by senior analysts or analyst teams are associated with higher market impact and more accurate estimates than those issued by their junior counterparts.

I continue to explore whether and how existing level of analyst coverage of underlying firms could affect the level of changes in synchronicity after recommendation revisions in the next step. As sell-side analysts provide firm-specific and market-wide information to investors, increasing analyst coverage usually implies better stock price informativeness in general, as seen in Crawford et al. (2012). If higher analyst coverage leads to better stock price informativeness, we should be able to observe a larger decrease in synchronicity after recommendation revisions for stocks with lower analyst coverage. To test this hypothesis, I sort all recommendation revisions based on the analyst coverage of underlying firms and conduct cross-sectional analysis. Indeed, firms with lower analyst coverage tend to experience larger decreases in synchronicity after recommendation revisions in general, after controlling for a series of relevant control variables and fixed effects. This suggests that recommendation revisions issued on firms with lower analyst coverage are associated with higher increases in price informativeness.

Loh and Stulz (2011) study the market impact of recommendation revisions issued by analysts and consider only recommendation revisions with statistically significant and visible market impact as "influential". They find that influential recommendation revisions are usually those issued by star analysts and with ratings further away from consensus. Based on their definition, I examine whether influential recommendation revisions are associated with larger decreases in synchronicity. Since downgrades are less likely to be information driven according to anchoring interpretation (see, for instance Li, Lin, and Lin, 2021), it seems natural to study the effect of influential recommendation revisions based on different subsamples. By conducting cross-sectional analyses separately within upgrade subsample and downgrade subsample, I show that influential recommendation upgrades are associated with more information content (larger decreases in synchronicity) and influential recommendation downgrades are associated with less information content (lower decreases in synchronicity) than non-influential ones. This result suggests that stock prices tend to incorporate more firm-specific information when analysts issue recommendation upgrades that are influential. While it's interesting to see that within downgrade subsamples, influential revisions are usually associated with less information content.

This paper contributes to literature in the following aspects. First, I contribute to the vast literature and heated discussion on relation between synchronicity and information environment by showing that synchronicity is inversely associated with amount of firm-specific information in Chinese stock market. This supports the theory of Roll (1988) that lower synchronicity indicates better stock price informativeness. Second, I introduce a new measure, namely the moving synchronicity measure, to examine the changes in price informativeness before and after analysts' recommendation revisions. This contributes to the literature on information leakage and sell-side analysts' behavior. This paper also contributes to the understanding of relationship between analyst characteristics and information content by conducting cross-sectional analyses on seniority, analyst coverage, and influential reports.

The rest of this paper proceeds as follows: In chapter 4.2 I introduce key literature in synchronicity, recommendation revisions, and other topics related to sell-side analysts. In chapter 4.3 I describe data and methodologies involved in this research. In chapter 4.4 I go through the main empirical results. I then present robustness tests in chapter 4.5. In chapter 4.6 I introduce some additional analyses that supplements the main results and conclude in chapter seven.

4.2 Literature review

In this section, I briefly introduce the literature relevant to this research. The literature introduced here is partitioned into three parts. First, I discuss literature regarding synchronicity. Second, I go through some key literature on recommendations and recommendation revisions issued by sell-side analysts. Finally, I introduce some other literature on sell-side analysts that's relevant to this research.

4.2.1 Synchronicity and price informativeness

Roll (1988) was among the pioneer to study the role of synchronicity in interpreting level of firm-specific information content and price informativeness. He suggests that R-squared derived from regression using individual stock returns and market returns, or synchronicity, measures the level of firm-specific information incorporated into stock prices. Higher R-squared value indicates lower level of firm-specific information. Based on the assumption that synchronicity indicates price informativeness, Piotroski and Roulstone (2004) examine different types of information that different market participants tend to provide. They find that synchronicity, or R-squared, is positively associated with the activities of sell-side analysts and negatively associated with trading activities of insiders. This suggests that sell-side analysts' activities tend to decrease the level of firm-specific information, meanwhile insiders' trading activities tend to increase the level of firm-specific information incorporated into stock prices. In a later research, Crawford et al. (2012) separate the first analysts to initiate coverage on listed firms from those subsequent analysts that initiate coverage on firms that are already covered by other analysts. Using synchronicity as measure of firm-specific information, they document that those first analysts to initiate coverage tend to provide more market-wide and industry-wide information instead of firm-specific information, whereas the subsequent analysts tend to provide more firm-specific information so that their research could stand out and add value. Hutton, Marcus, and Tehranian (2009) show opaque firms with higher level earnings management are usually associated with higher level of synchronicity and are more vulnerable to stock price crashes. Their results are in line with the theory that synchronicity is negatively associated with level of firm-specific information incorporated into stock prices.

On the other hand, Chan and Chan (2014) argue that synchronicity, proxied by natural log transformation of R-squared values, is actually positively associated with price informativeness instead. They examine the relationship between synchronicity and seasoned equity offering (SEO) discounts and show higher synchronicity leads to lower SEO discounts. They also document that analyst coverage could mitigate such negative relation. Their research supports the theory that higher synchronicity reflects better stock price informativeness. Devos et al. (2015) contribute to this strand of literature by showing that firms with lower synchronicity level experience stronger market reaction on trading volume, bid-ask spread, abnormal return, and return volatility when their recommendation rating level issued by sell-side analysts change. This result shows synchronicity is positively associated with price informativeness.

Unlike literature discussed above, Xing and Anderson (2011) claim that synchronicity, or R-squared, could indicate either higher or lower level of firm-specific information and relation between synchronicity and public information is inversely U-shaped. Based on their finding, they further show that synchronicity is not a proper and uniform indicator of information environment.

Instead of using R-squared or logit transformation of R-squared from regressions as measure of synchronicity, Huang et al. (2019) choose to use co-movement between individual stock returns and market returns as measure of synchronicity instead. They find that when investors are attracted by natural event such as large jack-pot lotteries and focus less on financial market, they intentionally and rationally choose to allocate more attention to market-wide information instead of firm-specific information.

4.2.2 Recommendations and recommendation revisions

Womack (1996) was among the pioneers to study the real effect of analyst recommendation revisions on financial market. He shows that both recommendation upgrades and downgrades issued by sell-side analysts employed by major U.S. brokerage houses are associated with significant abnormal returns, thus proving the stock-picking and market-timing abilities of sell-side analysts. Instead of studying recommendation revisions issued by individual sell-side analysts, Barber et al. (2001) focus on the recommendation consensus instead. They document that long-short portfolio based on recommendation consensus, with timely rebalancing based on recommendation revisions, yield a higher than 4 percent abnormal return on yearly basis. Ivkovic and Jegadeesh (2004) study the change of information content for both recommendation revisions as well as earning forecast revisions within each quarter. They find that recommendations and forecast revisions within one week after earnings announcements are least informative and level of informativeness tend to increase over time within the quarter. Barbera et al. (2006) examine the relationship between the distribution of existing recommendation ratings and the profitability of recommendation revisions. They find that recommendation revisions issued by sell-side analysts working for brokerage houses with lower percentage of existing buy-ratings are more profitable than revisions issued by their counterparts working for brokerage houses with higher percent of existing buy-ratings. They also find that percentage of buy-ratings within all recommendation ratings gradually decreased from mid-2000 in U.S. market, potentially due to the implementation of NASD Rule 2771.

Jegadeesh et al. (2004) evaluate the detailed characteristics of recommended firms (such as momentum, growth, and value) and how these characteristics affect the profitability of recommendations issued by sell-side analysts. They find that consensus recommendations only add value when the firms recommended come with positive characteristics, such as positive momentum, and high value. Naively following the recommendations issued by sell-side analysts could potentially end up with negative abnormal returns if characteristics of recommended firms are ignored. Instead of purely focusing on U.S. financial market, Jegadeesh and Kim (2006) study the value of sell-side analysts' recommendations in different G7 countries. They find that recommendation revisions are associated with significant abnormal returns in all countries except for Italy, whereas the United States exhibits the largest price reaction and post recommendation revision price drift among G7 countries. Their research seems to show the value of recommendation revisions issued by sell-side analysts are significant and robust even outside U.S. market.

4.2.3 Other literature on sell-side analysts

With a proprietary panel dataset, Maber et al. (2021) try to categorize and quantify the behavior and activities of sell-side analysts and investigate how they build and sustain the business relations with buy-side institutional clients. They find that high-touch phone calls and roadshows are crucially important in helping them to maintain buy-side customer relations.

Instead of examining all recommendation revisions, Christophe et al. (2010) focus their research on downgrades issued by sell-side analysts and study the behavior of short-sellers prior to the actual release of downgrades. They document abnormal level of short-selling trades in the three-day window before the actual public announcement of downgrades and that such abnormal level of short-selling trades is associated with subsequent price reaction after the actual public announcement of downgrades. Their research seems to show that sell-side analysts don't always keep their pending recommendation revisions in secrecy until actual public announcements.

Loh and Stulz (2011) take a different approach in studying recommendation revisions and define "influential" recommendation revisions as those visibly affect the stock market prices of the target firms. They define influential recommendation revisions as those associated with significant market impact, namely above the 5% threshold which corresponds to two standard deviations. They document 12% of all recommendation revisions to be influential according to such definition and find that influential recommendation revisions are more likely to come from star analysts, former influential analysts, and leaders.

Li et al. (2021) study the anchoring bias of sell-side analysts by examining the recommendation downgrades issued near 52-week high. They find that analysts are more likely to downgrade stocks that are approaching 52-week high. These downgrades are usually less profitable than the normal downgrades and are less likely to be associated with subsequent earnings forecast revisions. These results show that analysts are affected by anchoring bias and their recommendation revisions near 52-week high are less likely to be information driven.

4.3 Data and methodologies

In this section, I introduce the sample construction process and variable definitions of this research in detail. First, I go through the sample of this research. Next, I show how key variables of the empirical tests in this research are constructed. Finally, I examine the empirical test designs and summary statistics.

4.3.1 Data and sample construction

I start with all recommendations from 2010 to 2020 in Chinese stock market according to CSMAR recommendations dataset. Sell-side analysts issued 546,089 forecast reports (with recommendation ratings such as “buy” and “sell”) from 2010 to 2020 in Chinese stock market documented by CSMAR with unique report IDs, but only 19,963 were recommendation revisions (upgrades and downgrades). Within these 19,963 recommendation revisions, 12,383 were upgrades and the remaining 7,580 were downgrades, involving 2,571 unique firms. I further adjust the recommendation revision dates to the next available trading day if these revisions were made on weekends or after trading hours in weekdays. I then calculate synchronicity, or R-squared of regression, before and after recommendation revisions based on 45 trading days prior and post each recommendation revision respectively. Hence, there're two synchronicity values for each recommendation revisions representing prior and post event values. I further delete those synchronicity values calculated based on less than 30 valid trading days and make sure each recommendation revisions in the sample comes with valid synchronicity value pairs prior and post event. At this stage the sample consists of 36,852 synchronicity values, representing 18,462 unique recommendation revisions.

4.3.2 Variables in this research

To calculate the two R-squared values (before and after event) for each recommendation revision, I run regression based on individual stock returns and market index returns. I use CSI 300 index as the market index since it represents approximately 70% of market capital in Chinese stock market and is generally accepted as a good measure of market returns. To calculate R-squared before each event, I take the 45 trading days from 50 trading days before revision date to 6 trading days before revision date, which corresponds to [-50, -6]. To calculate R-squared after each event, I take the 45 trading days from 6 trading days after revision date to 50 trading days after revision date, corresponding to [6, 50]. R-squared values calculated from regressions between individual stock returns and market returns with higher than 30 observations are considered as valid, and labeled *R-squared.(45)*. Furthermore, I only keep recommendation revisions with valid R-squared value in pairs within our sample. For robustness check, I also calculate R-squared without excluding 5 trading days both before and after revision date, which corresponds to [-45,-1] and [1,45], and label it *R-squared.(Robust)*. Other measures of synchronicity values, including *R-squared.(30)* and *R-squared.(60),* are calculated in the similar way as in *R-squared.(45),* with minimum of 20 trading days and 45 trading days as qualified for calculating R-squared values respectively. Correlation coefficient between individual stock returns and market index returns is calculated in the similar way as in *R-squared.(45)*, with [-50, -6] trading window for pre-revision correlation coefficient and [6, 50] trading window for post-revision correlation coefficient, and labeled *Correlation*.

After revisions is an indicator variable that equals to one if a synchronicity value is calculated after recommendation revision date and equals to zero if otherwise. Size is the total market value of the target firm of each recommendation revision on the revision announcement date. *Turnover.(30), Turnover.(45)*, and *Turnover.(60)* are the 30 trading days, 45 trading days, and 60 trading days turnover rate for each stock before recommendation revisions respectively. *Past-return.(30)*, *Past-return.(45),* and *Past return.(60)* represent cumulative total return in the past 30 trading days, 45 trading days, and 60 trading days before recommendation revisions respectively. *BM ratio* indicates the book to market ratio of the target firm based on the latest available full financial year's book value and the market value on the recommendation revision announcement date. *RoE* is the return on equity ratio, which is calculated based on the latest available full financial year's book value of equity and net income. *STDDEV* represents the return standard deviation of the target firm, calculated based on the firm's daily returns of the previous year. *Ln(Analyst coverage)* is the natural log of analyst coverage for the target firm in the previous year.

Senior is an indicator variable and equals to one if the recommendation revision is issued by a senior analyst (team). Seniority of analysts is ranked based on the number of days an analyst appeared in the CSMAR dataset, in the similar fashion defined as in previous chapter. Recommendation revisions issued by individual analyst with upper-half seniority ranking (or by analyst teams with upper-half mean seniority ranking) are assigned *Senior* equals to one. *Low coverage* is also an indicator variable, which equals to one if a recommendation revision is issued on a firm with analyst coverage that's lower than the sample median. Influential indicates whether a recommendation revision is considered as influential recommendation revision in the market (see Loh and Stulz, 2011). A recommendation upgrade (downgrade) is considered "influential" if the two-days cumulative abnormal return is larger than the $2 \times 1.96 \times \sqrt{\text{idiosyncratic volatility}}$. The idiosyncratic volatility, or standard deviation of residuals, is calculated from regression of three-month daily stock returns against Fama-French three factors. According to this definition, only those revisions that generates a statistically significant (with P-values lower than 5%) return on the two-day window starting from the announcement date are considered influential and with material market impact. Here in this research, I make minor adjustments to the process of identifying influential revisions accordingly. Instead of comparing two days cumulative returns, I compare eleven trading days instead, since I'm excluding 5 trading days both before and after recommendation revisions when calculating synchronicity values. If the eleven-days cumulative abnormal return is larger than the $11 \times 1.96 \times \sqrt{\text{idiosyncratic volatility}}$ considering the direction of revision, it is considered as Influential recommendation revision. Influential recommendation revisions are therefore assigned Influential equal to one.

4.3.3 Methodology and empirical test design

In the main analysis, I examine how synchronicity changes after recommendation revisions with regression tests. To be specific, I conduct the following regression test specified as the

$$Rsquared.(T) = \alpha_0 + \beta \times After\ Revisions + \gamma \times X + \varepsilon \qquad (1)$$

R-squared.(T) is synchronicity values calculated based on T trading days, with T equals 30, 45, or 60. After revisions is an indicator variable that equals to one if the synchronicity value is calculated after recommendation revisions and zero if otherwise, as discussed in the previous section. X is the vector of controls, including market size, book-to-market ratio, past return, turnover rate, analyst coverage, return standard deviation, and return on equity. ε is the error term.

In additional analyses, I examine how the change in synchronicity is affected by other factors with cross-sectional regression tests. To be specific, I conduct the following regression tests specified as:

$$Rsquared.(T) = \alpha_0 + \beta \times After\ Revisions \times Senior + \beta 1 \times After\ revisions + \beta 2 \times Senior + \gamma \times X + \varepsilon \qquad (2)$$

$$Rsquared.(T) = \alpha_0 + \beta \times After\ Revisions \times High\ Coverage + \beta 1 \times After\ revisions + \beta 2 \times High\ Coverage + \gamma \times X + \varepsilon \qquad (3)$$

$$Rsquared.(T) = \alpha_0 + \beta \times After\ Revisions \times Influential + \beta 1 \times After\ revisions + \beta 2 \times Influential + \gamma \times X + \varepsilon \qquad (4)$$

R-squared. (T), After revisions, and control variables are defined in the same way. *Senior, High coverage,* and *Influential* are indicator variables that equals to one if a recommendation revision is issued by a senior analyst (or a senior analyst team), on a firm with high analyst coverage, and considered as "influential" respectively, defined in the previous section. X is the vector of controls, including market size, book-to-market ratio, past return, turnover rate, analyst coverage, return standard deviation, and return on equity. ε is the error term.

4.3.4 Description of data

Table 1 shows the summary statistics of all recommendation revisions (upgrades and downgrades) included in our sample, between 2010 and 2020. On average, the mean of *R-squared. (45)* is around 0.322, with standard deviation equals 0.207. As a different measure of synchronicity, *Correlation* has a mean of 0.528 and a standard deviation of 0.207. The underlying firms of recommendation revisions has a mean market value equals to around 35.4 billion CNY on the date of revision announcement, with standard deviation equals to 105.7 billion CNY. The mean turnover rate for 30, 45, and 60 trading days prior to recommendation revisions are 0.409, 0.599, and 0.78 respectively. The mean past return within the 30, 45, and 60 trading days prior to recommendation revisions are 0.044, 0.057, and 0.066 respectively. Book to market ratio calculated with the latest available financial year-end book value and market value on the revision announcement date has a mean value of 0.466. The return on equity calculated with the latest available net income and book value has a mean of 0.115. The mean value of daily return standard deviations calculated in the year prior to recommendation revision announcement date equals 0.028. The mean value of analyst coverage equals to 15.7 in the year prior to recommendation revision announcement.

4.4 Main results

In this section, I introduce the main results of our analyses. First, I examine the relation between change in synchronicity and recommendation revision to show that lower synchronicity indicates more firm-specific information incorporated into stock prices. Next, I introduce the "Moving R-squared" results as showed in Figure 1 and interpret how this figure explains the potential leak of information before the actual revision announcement dates.

4.4.1 Changes in synchronicity after recommendation revisions

I first introduce the changes in synchronicity after recommendation revisions, proxied by R-squared of regressions between individual stock returns and market index returns. As Table 2 shows, synchronicity after recommendation revisions is significantly lower than synchronicity before recommendation revisions in general, after controlling for size, book to market ratio, past return, return standard deviations, return on equity, turnover rate, analyst coverage, as well as year and brokerage houses fixed effects. The change in synchronicity is economically large too, with mean decrease of around 1.12% in R-squared, representing an overall higher than 3.5 percentage point change. Since we're already aware that sell-side analysts tend to provide firm-specific information when they issue recommendation revisions through communication with buy-side institutional investors during roadshows and phone calls, this result indicates that lower synchronicity suggests more firm-specific information incorporated into stock prices, in line with the theory of Roll (1988).

4.4.2 Moving synchronicity

To further understand how and when firm-specific information provided by sell-side analysts is incorporated into stock prices before and after recommendation revisions on a daily basis, I calculate an R-squared value for each trading date from 80 trading days before each recommendation revision announcement date to 80 trading days after it. This result is showed in Figure 1 and named “Moving R-squared”. The R-squared values are calculated in the similar fashion as introduced in Section 4.3.2, with 45 trading days after each starting date. For instance, R-squared values calculated on date T=-80, which corresponds to 80 trading days before recommendation revision announcement date, were based on daily returns between -80 and -36 (the 45 days window [-80, -36]). Each R-squared value measures the amount of firm-specific information using stock returns of the next 45 trading days, providing an opportunity to observe the change in firm-specific information level day by day. From Figure 1, it seems obvious that decrease in synchronicity starts from around day -60, indicating that level of firm-specific information starts to increase as early as 15 trading days before recommendation revisions are actually announced (the synchronicity of day T=-60 is calculated using trading days [-60, -16]). This result seems to support the finding of Christophe et al. (2010) that sell-side analysts start leaking information about their recommendation revisions days before actual announcements. Level of firm-specific information peaked around day T=0 and starts to decrease from day T=0 on. The change in firm-specific information associated with recommendation revisions slowly wears out and the effect almost completely vanishes around 30 days after announcement.

4.5 Robustness check

In this section, I conduct a few more sets of regression tests as robustness checks to my main analysis. First, I re-calculate R-squared values before and after recommendation revisions without excluding 5 trading days both before and after announcement days and repeat my main regression test. Second, I use correlation coefficient as a second measure of synchronicity instead of R-squared and conduct the same regression test. Third, I calculate R-squared values using 30 daily returns and 60 daily returns instead of 45 as in the main analysis and repeat the regression. The results of all these tests remain negative and statistically significant as in my main analysis.

4.5.1 Without excluding 5 daily returns around announcements

As a different way to calculate synchronicity, I directly use 45 daily returns right before and after recommendation revision announcement dates to calculate R-squared values without excluding the 5 trading days before and after revision dates respectively, and label it *R-squared. (Robust)*. To be more specific, *R-squared. (Robust)* is calculated based on trading days [-46, -1] for before revision values and [1,46] for after revision values. I then repeat the regression analysis as in my main tests and show the results in Table 3. The coefficients for After revisions are still statistically significant and negative, although decreased a bit in magnitude. This result suggests that my main result in Section 4.4.1 is robust even if daily returns around revision announcement days are not excluded when calculating R-squared values.

4.5.2 Correlation Coefficient as a second measure

R-squared of regression tests is not the only proxy for synchronicity generally used in literature. Both Huang et al. (2019) and Li et al. (2022) choose correlation coefficient as a different proxy for synchronicity instead. In this section, I calculate correlation coefficients before and after announcement days with individual stock returns and market index returns for each recommendation revision. As in the calculation of *R-squared. (45)*, I exclude the returns for 5 trading days both before and after announcement days, easing the concern that changes in synchronicity are driven by the abnormal returns around announcement days. Then I conduct the same regression analysis as in the main test, with *Correlation* as dependent variable instead of *R-squared. (45)* and report the results in Table 4. As the coefficients of After revisions indicates, correlation coefficients significantly decrease after recommendation revisions, controlling for size, book to market ratio, past return, return standard deviations, return on equity, turnover rate, analyst coverage, as well as year and brokerage fixed effects. This result suggests that synchronicity indeed decreases after recommendation revisions, even if using correlation coefficient as proxy for synchronicity instead of the usual R-squared measure.

4.5.3 Different choice of R-squared values

To mitigate the concern that choosing to use 45 trading days when calculating R-squared is somewhat arbitrary, I calculate two other R-squared measures with 30 trading days and 60 trading days respectively instead. For *R-squared. (30)*, I use trading days [6, 35] to calculate after revision R-squared values and trading days [-35, -6] to calculate before revision R-squared values. For *R-squared. (60)*, I use trading days [6, 65] to calculate after revision R-squared values and trading days [-65, -6] to calculate before revision R-squared values. Then I run the same regression test as in the main analysis, with *R-squared. (30)* and *R-squared. (60)* as dependent variable instead of *R-squared. (45)* controlling for proper control variables and fixed effects. The results are reported in Table 5 Panel A and B. In both Panel A and Panel B, the coefficients of After revisions are statistically significant and negative. This result indicates that synchronicity significantly decreases after recommendation revisions, even if using 30 trading days or 60 trading days to calculate R-squared values instead of 45 trading days. The main result of my analysis remains robust when choosing different number of trading days to calculate R-squared values.

4.6 Additional analyses

To further understand the changes in firm-specific information after recommendation revisions using synchronicity, I design the following cross-sectional analyses and report the results in the sections 4.6.1, 4.6.2, and 4.6.3. First, I examine whether recommendation revisions issued by senior analysts (or analyst teams) contain higher level of firm-specific information comparing to those issued by non-senior analysts (or analyst teams). Then I check whether recommendation revisions issued on firms with lower existing analyst coverage provides relatively higher level of firm-specific information comparing to those revisions issued on firms with higher existing analyst coverage. Finally, I examine whether "influential" recommendation revisions with significant and visible market impact tend to provide more firm-specific information.

4.6.1 Cross-sectional test on Senior vs. Non-senior

In the main analysis, I show that lower synchronicity is associated with higher level of firm-specific information incorporated into stock prices by comparing the change in synchronicity before and after recommendation revisions. One interesting topic to explore the next is, whether recommendation revisions issued by senior analysts or analyst teams contain relatively more firm-specific information comparing to those issued by non-senior analysts or non-senior analyst teams. To explore this topic, I sort all recommendation revisions within sample based on the average seniority scores they received. The seniority ranking score of individual analysts in a particular quarter is calculated in the procedure explained in Section 4.3.2. Recommendation revisions issued by analysts or analyst teams with upper-half seniority scores are considered as issued by senior analysts and assigned Senior equals to one, whereas the remaining recommendation revisions are assigned zeros. Then I conduct the regression test as in equation (2) and report the results in Table 6. Since the coefficients for After revisions × Senior are statistically significant and negative for all four columns, it seems that recommendation revisions issued by senior analysts or analyst teams indeed contains more firm-specific information than their non-senior counterparts.

4.6.2 Cross-sectional test on High coverage vs. Low coverage

The natural question to explore next, is whether recommendation revisions issued on firms with high analyst coverage provides less marginal firm-specific information comparing to those firms with low analyst coverage. The idea is that firms with high analyst coverage are already better explored and contains more firm-specific information than firms with low analyst coverage to start with, therefore the marginal contribution provided by a recommendation revision might be limited. I sort all recommendation revisions within sample based on the analyst coverage of their underlying target firms. The detailed definition of analyst coverage is explained in Section 4.3.2. Recommendation revisions issued on underlying target firms with upper-half analyst coverage are considered as issued on high analyst coverage firms and assigned Low coverage equals to one. I then run the regression test as in equation (3) and report the results in Table 7. The negative and statistically significant coefficients for all four columns of After revisions × Low coverage suggest that recommendation revisions issued on firms with high analyst coverage provide relatively lower level of firm-specific information.

4.6.3 Cross-sectional test on Influential vs. Noninfluential revisions

Loh and Stulz (2011) define recommendation revisions as "influential", if the two-days cumulative abnormal return is larger than the $2 \times 1.96 \times \sqrt{\text{idiosyncratic volatility}}$. Where idiosyncratic volatility, or standard deviation of residuals, is calculated from regression of three-month daily stock returns against Fama-French three factors. Influential revisions are those generate statistically significant (with P-values lower than 5%) abnormal returns comparing to the daily returns of previous 3 months. Instead of comparing the two-days cumulative returns, I compare the cumulative abnormal returns of eleven trading days before and after revision announcement days instead, since I'm excluding 5 trading days both before and after recommendation revisions when calculating synchronicity values. Influential recommendation revisions represent approximately 12.76% of recommendation revisions in the full sample. It's natural to assume that these influential recommendation revisions should provide more firm-specific information comparing to those non-influential revisions, since stock prices react faster and stronger on information provided by such revisions.

Based on this hypothesis, I conduct the regression test as in equation (4) and report the results in Table 8, with definition of indicator variable Influential explained in Section 4.3.2. Since investors tend to react differently toward recommendation upgrades and downgrades with different emotional status and behavioral biases, I conduct the analyses separately for subsamples consisting of upgrades and downgrades respectively. In Panel A, coefficients of After revisions × Influential are negative, suggesting that influential upgrades contain more firm-specific information in general. Whereas in Panel B, coefficients of After revisions × Influential are positive, suggesting that influential downgrades contain less firm-specific information. One possible explanation for such difference is that investors usually need to digest more firm-specific information and consider carefully before making a purchase upon seeing an upgrade revision. On the other hand, downgrade revisions could potentially lead to mass panic and fire-sell of investors, leaving investors no time nor interests to digest enough firm-specific information before making investment decisions.

4.7 Conclusion

In this research, I find evidence suggesting that lower synchronicity indicates higher amount of firm-specific information incorporated into stock prices, and thus better price informativeness. I study the change of synchronicity around recommendation revisions issued by sell-side analysts, which usually associate with distribution of new firm-specific information about the target firm. Synchronicity of target underlying firms significantly decreases after recommendation revisions, suggesting an negative relationship between amount of firm-specific information incorporated into stock prices and synchronicity. By plotting the change of R-squared on daily basis before and after recommendation revision announcement days, I find the decrease in synchronicity in general starts around 15 trading days ahead of actual announcements of revisions. This evidence suggests the potential leak of valuable firm-specific information from sell-side analysts before the actual announcement days.

My research also shows that recommendation revisions issued by senior analysts (teams) and those issued on firms with lower analyst coverage contain more firm-specific information. I also find evidence to show that influential revisions contain more firm-specific information within upgrade subsample, whereas influential revisions contains less firm-specific information within downgrade subsample.

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Figure 1: Moving R-squared

The R-squared values are calculated in the similar fashion as introduced in Section 3.2, with 45 trading days after each starting date. For instance, R-squared values calculated on date T=-80, which corresponds to 80 trading days before recommendation revision announcement date, were based on daily returns between -80 and -36 (the 45 days window [-80, -36]). Each R-squared value measures the amount of firm-specific information using stock returns of the next 45 trading days, providing an opportunity to observe the change in firm-specific information level day by day.

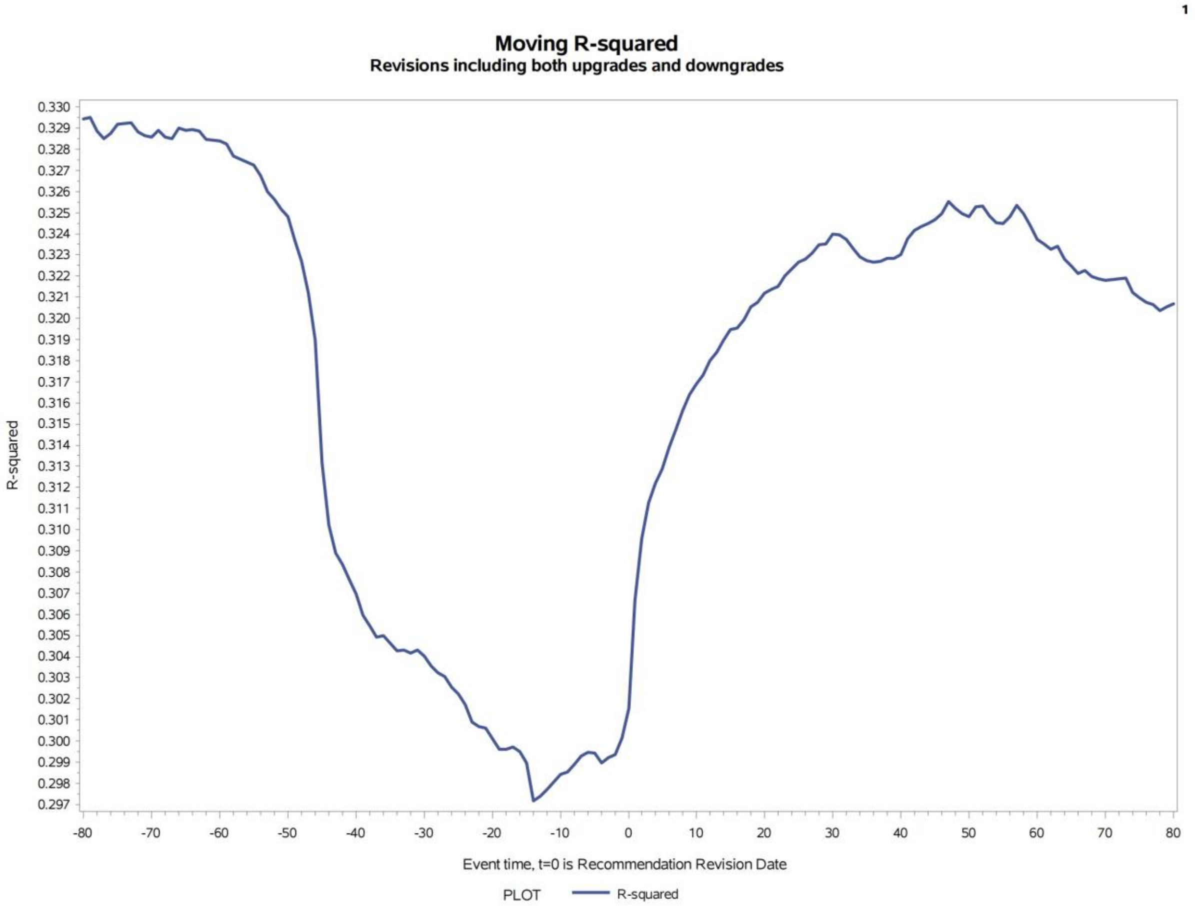

Table 1: Summary Statistics

This table shows the summary statistics for the observations in the sample. *R-squared. (45), R-squared. (Robust), R-squared. (30), R-squared. (60)* are the R-squared values of regressions calculated with daily stock returns and daily market returns both before and after recommendation revisions. *Correlation* is calculated as the correlation coefficient between daily stock returns and the market index returns before and after recommendation revisions. *Mve. (Billion)* is the market value of firm in billions of CNY at recommendation revision announcement date. *Turnover. (45), Turnover. (30), Turnover. (60)* are calculated as the trading volume divided by the number of shares outstanding for 45, 30 and 60 trading days before recommendation revisions respectively. *Past return. (45), Past return. (30), Past return. (60)* are the cumulative 45, 30, and 60 daily returns before recommendation revisions respectively. *STDDEV* is the standard deviation of daily stock returns in the year before recommendation revisions. *BM ratio* is the book to market ratio, with book value taken from the most recent financial year-end, and market value taken on the recommendation revision announcement date. *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. *Senior, Low coverage, Influential* are indicator variables that equals to one if a recommendation revision is issued by senior analyst (team), on a firm with low analyst coverage, or is considered influential respectively.

	Mean	Std	p10	p50	p90
Synchronicity					
R-squared. (45)	0.322	0.207	0.059	0.299	0.621
R-squared. (Robust)	0.317	0.206	0.058	0.291	0.616
R-squared. (30)	0.33	0.221	0.049	0.303	0.649
R-squared. (60)	0.32	0.199	0.069	0.297	0.605
Correlation	0.528	0.207	0.242	0.546	0.788
Firm characteristics					
Mve. (Billion)	35.41	105.735	3.391	11.132	67.648
Turnover. (45)	0.599	0.526	0.147	0.441	1.236
Past return. (45)	0.057	0.201	-0.175	0.045	0.303
Turnover. (30)	0.409	0.371	0.097	0.298	0.851
Past return. (30)	0.044	0.168	-0.15	0.034	0.251
Turnover. (60)	0.78	0.671	0.197	0.582	1.603
Past return. (60)	0.066	0.228	-0.198	0.053	0.341
BM ratio	0.466	1.024	0.124	0.326	0.869
RoE	0.115	0.156	0.034	0.109	0.216
STDDEV	0.028	0.008	0.018	0.026	0.038
Analyst coverage	15.701	9.219	4	15	28
Senior	0.496	0.5	0	0	1
Low coverage	0.478	0.5	0	0	1
Influential	0.128	0.334	0	0	1
N	36,856				

Table 2: Change in R-squared after recommendation revisions

The dependent variable is *R-squared. (45)*, the R-squared values calculated based on individual stock returns and market index returns for 45 trading days before or after recommendation revisions while excluding the trading days around announcement dates respectively. *After revisions* is an indicator variable that equals to one if an R-squared value is calculated based on returns after recommendation revision. Broker fixed effects are based on the unique brokerage houses codes provided by CSMAR. Year fixed effects are based on the year that recommendation revisions are announced. The sample period is 2010-2020. Heteroscedasticity-consistent standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)
After revisions	-0.0104***	-0.0112***	-0.0112***	-0.0112***
	(0.0022)	(0.002)	(0.0019)	(0.0018)
Size		0.0166***	0.0280***	0.0276***
		(0.001)	(0.001)	(0.001)
Turnover rate		0.0246***	0.0131***	0.0129***
		(0.0023)	(0.0023)	(0.0023)
Past return		-0.2067***	-0.1928***	-0.1927***
		(0.0058)	(0.0054)	(0.0054)
BM ratio		0.1725***	0.1671***	0.1661***
		(0.0036)	(0.0033)	(0.0034)
ROE		0.1780***	0.0915***	0.0917***
		(0.0149)	(0.0136)	(0.0137)
STDDEV		1.6324***	1.3004***	1.2480***
		(0.1424)	(0.1737)	(0.1743)
Ln(Analyst coverage)		0.0242***	0.0088***	0.0093***
		(0.0015)	(0.0015)	(0.0015)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	36,856	35,288	35,288	35,288
*R*2	0.001	0.148	0.297	0.301

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

Table 3: R-squared without excluding trading days around announcements

The dependent variable is *R-squared. (Robust)*, the R-squared values calculated based on individual stock returns and market index returns for 45 trading days before or after recommendation revisions without excluding the trading days around announcement dates respectively. *After revisions* is an indicator variable that equals to one if an R-squared value is calculated based on returns after recommendation revision. Broker fixed effects are based on the unique brokerage houses codes provided by CSMAR. Year fixed effects are based on the year that recommendation revisions are announced. The sample period is 2010-2020. Heteroscedasticity-consistent standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)
After revisions	-0.0069***	-0.0076***	-0.0076***	-0.0076***
	(0.0021)	(0.002)	(0.0018)	(0.0018)
Size		0.0172***	0.0285***	0.0280***
		(0.001)	(0.001)	(0.001)
Turnover rate		0.0275***	0.0161***	0.0158***
		(0.0023)	(0.0023)	(0.0023)
Past return		-0.2396***	-0.2254***	-0.2256***
		(0.0057)	(0.0053)	(0.0054)
BM ratio		0.1684***	0.1627***	0.1617***
		(0.0035)	(0.0033)	(0.0034)
ROE		0.1749***	0.0876***	0.0879***
		(0.0148)	(0.0136)	(0.0136)
STDDEV		1.5260***	1.3069***	1.2478***
		(0.1409)	(0.1723)	(0.1729)
Ln(Analyst coverage)		0.0244***	0.0092***	0.0096***
		(0.0015)	(0.0014)	(0.0015)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	36,852	35,268	35,268	35,268
*R*2	0	0.16	0.304	0.308

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

Table 4: Correlation coefficient as a different measure of synchronicity

The dependent variable is *Correlation*, the correlation coefficients calculated based on individual stock returns and market index returns for 45 trading days before or after recommendation revisions while excluding the trading days around announcement dates respectively. *After revisions* is an indicator variable that equals to one if an R-squared value is calculated based on returns after recommendation revision. Broker fixed effects are based on the unique brokerage houses codes provided by CSMAR. Year fixed effects are based on the year that recommendation revisions are announced. The sample period is 2010-2020. Heteroscedasticity-consistent standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)
After revisions	-0.0116***	-0.0125***	-0.0125***	-0.0125***
	(0.0022)	(0.0021)	(0.0018)	(0.0018)
Size		0.0105***	0.0228***	0.0224***
		(0.001)	(0.001)	(0.001)
Turnover rate		0.0229***	0.0122***	0.0118***
		(0.0024)	(0.0023)	(0.0023)
Past return		-0.1905***	-0.1789***	-0.1788***
		(0.0058)	(0.0054)	(0.0054)
BM ratio		0.1640***	0.1543***	0.1536***
		(0.0036)	(0.0033)	(0.0034)
ROE		0.1826***	0.0834***	0.0830***
		(0.015)	(0.0136)	(0.0137)
STDDEV		1.3441***	0.9415***	0.8909***
		(0.143)	(0.1733)	(0.1739)
Ln(Analyst coverage)		0.0260***	0.0096***	0.0102***
		(0.0015)	(0.0015)	(0.0015)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	37,034	35,454	35,454	35,454
$R2$	0.001	0.129	0.292	0.296

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

Table 5: R-squared calculated with different number of days

The dependent variable in Panel A is *R-squared. (30)*, the R-squared values calculated based on individual stock returns and market index returns for 30 trading days before or after recommendation revisions while excluding the trading days around announcement dates respectively. The dependent variable in Panel B is *R-squared. (60)*, the R-squared values calculated based on individual stock returns and market index returns for 60 trading days before or after recommendation revisions while excluding the trading days around announcement dates respectively. *After revisions* is an indicator variable that equals to one if an R-squared value is calculated based on returns after recommendation revision. Broker fixed effects are based on the unique brokerage houses codes provided by CSMAR. Year fixed effects are based on the year that recommendation revisions are announced. The sample period is 2010-2020. Heteroscedasticity-consistent standard errors are shown in parentheses.

Panel A: 30 trading days

	(1)	(2)	(3)	(4)
After revisions	-0.0073***	-0.0080***	-0.0080***	-0.0080***
	(0.0023)	(0.0022)	(0.0021)	(0.0021)
Size		0.0119***	0.0243***	0.0240***
		(0.0011)	(0.0011)	(0.0011)
Turnover rate		0.0152***	0.0041	0.0038
		(0.0036)	(0.0036)	(0.0036)
Past return		-0.2045***	-0.2044***	-0.2045***
		(0.0074)	(0.0071)	(0.0071)
BM ratio		0.1803***	0.1720***	0.1707***
		(0.0039)	(0.0037)	(0.0037)
ROE		0.1910***	0.0990***	0.0983***
		(0.0162)	(0.0151)	(0.0152)
STDDEV		1.9633***	1.6343***	1.5875***
		(0.154)	(0.1916)	(0.1923)
Ln(Analyst coverage)		0.0262***	0.0110***	0.0114***
		(0.0017)	(0.0016)	(0.0016)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	36,766	35,170	35,170	35,170
*R*2	0	0.12	0.244	0.249

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

Panel B: 60 trading days

	(1)	(2)	(3)	(4)
After revisions	-0.0061***	-0.0070***	-0.0070***	-0.0070***
	(0.0021)	(0.0019)	(0.0017)	(0.0017)
Size		0.0196***	0.0304***	0.0299***
		(0.0009)	(0.001)	(0.001)
Turnover rate		0.0281***	0.0156***	0.0153***
		(0.0018)	(0.0017)	(0.0017)
Past return		-0.1942***	-0.1888***	-0.1889***
		(0.0049)	(0.0046)	(0.0046)
BM ratio		0.1664***	0.1590***	0.1583***
		(0.0034)	(0.0031)	(0.0032)
ROE		0.1552***	0.0683***	0.0681***
		(0.0142)	(0.0128)	(0.0128)
STDDEV		1.3546***	0.8662***	0.8156***
		(0.1359)	(0.163)	(0.1634)
Ln(Analyst coverage)		0.0249***	0.0084***	0.0091***
		(0.0015)	(0.0014)	(0.0014)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	36,730	35,236	35,236	35,236
$R2$	0	0.166	0.333	0.338

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

Table 6: Seniority and changes in synchronicity

The dependent variable is *R-squared. (45)*, the R-squared values calculated based on individual stock returns and market index returns for 45 trading days before or after recommendation revisions while excluding the trading days around announcement dates respectively. *Senior* is an indicator variable that equals to one if a recommendation revision is issued by a senior analyst or senior analyst team. *After revisions* is an indicator variable that equals to one if an R-squared value is calculated based on returns after recommendation revision. Broker fixed effects are based on the unique brokerage houses codes provided by CSMAR. Year fixed effects are based on the year that recommendation revisions are announced. The sample period is 2010-2020. Heteroscedasticity-consistent standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)
After revisions × Senior	-0.0087**	-0.0079*	-0.0079**	-0.0079**
	(0.0043)	(0.0041)	(0.0037)	(0.0037)
After revisions	-0.0061**	-0.0073**	-0.0073***	-0.0073***
	(0.003)	(0.0029)	(0.0026)	(0.0026)
Senior	0.0094***	0.0049*	0.0039	0.0037
	(0.003)	(0.0029)	(0.0026)	(0.0027)
Size		0.0166***	0.0280***	0.0276***
		(0.001)	(0.001)	(0.001)
Turnover rate		0.0246***	0.0131***	0.0129***
		(0.0023)	(0.0023)	(0.0023)
Past return		-0.2066***	-0.1928***	-0.1927***
		(0.0058)	(0.0054)	(0.0054)
BM ratio		0.1725***	0.1671***	0.1661***
		(0.0036)	(0.0033)	(0.0034)
ROE		0.1781***	0.0915***	0.0917***
		(0.0149)	(0.0136)	(0.0137)
STDDEV		1.6314***	1.3004***	1.2477***
		(0.1424)	(0.1738)	(0.1743)
Ln(Analyst coverage)		0.0242***	0.0088***	0.0093***
		(0.0015)	(0.0015)	(0.0015)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	36,856	35,288	35,288	35,288
*R*2	0.001	0.148	0.297	0.301

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

Table 7: Analyst coverage and changes in synchronicity

The dependent variable is *R-squared. (45)*, the R-squared values calculated based on individual stock returns and market index returns for 45 trading days before or after recommendation revisions while excluding the trading days around announcement dates respectively. *Low coverage* is an indicator variable that equals to one if a recommendation revision is issued on a firm with lower analyst coverage. *After revisions* is an indicator variable that equals to one if an R-squared value is calculated based on returns after recommendation revision. Broker fixed effects are based on the unique brokerage houses codes provided by CSMAR. Year fixed effects are based on the year that recommendation revisions are announced. The sample period is 2010-2020. Heteroscedasticity-consistent standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)
After revisions × Low Coverage	-0.0090**	-0.0084**	-0.0084**	-0.0084**
	(0.0043)	(0.0041)	(0.0037)	(0.0037)
After revisions	-0.0061**	-0.0071**	-0.0071***	-0.0071***
	(0.003)	(0.0029)	(0.0026)	(0.0026)
Low Coverage	-0.0456***	-0.0168***	-0.000	-0.000
	(0.003)	(0.0038)	(0.0034)	(0.0034)
Size		0.0162***	0.0278***	0.0274***
		(0.001)	(0.001)	(0.001)
Turnover rate		0.0245***	0.0131***	0.0129***
		(0.0023)	(0.0023)	(0.0023)
Past return		-0.2054***	-0.1924***	-0.1923***
		(0.0058)	(0.0054)	(0.0054)
BM ratio		0.1738***	0.1674***	0.1665***
		(0.0036)	(0.0033)	(0.0034)
ROE		0.1757***	0.0913***	0.0915***
		(0.0149)	(0.0136)	(0.0137)
STDDEV		1.7055***	1.3152***	1.2626***
		(0.1427)	(0.174)	(0.1746)
Ln(Analyst coverage)		0.0144***	0.0069***	0.0074***
		(0.0021)	(0.002)	(0.002)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	36,856	35,288	35,288	35,288
*R*2	0.015	0.149	0.297	0.301

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

Table 8: Influential revisions and changes in synchronicity

Panel A consists of only upgrade recommendation revisions, whereas Panel B consists of only downgrade recommendation revisions. The dependent variable for both panels are *R-squared. (45)*, the R-squared values calculated based on individual stock returns and market index returns for 45 trading days before or after recommendation revisions while excluding the trading days around announcement dates respectively. *Influential* is an indicator variable that equals to one if a recommendation revision is considered to be influential with significant market impact. *After revisions* is an indicator variable that equals to one if an R-squared value is calculated based on returns after recommendation revision. Broker fixed effects are based on the unique brokerage houses codes provided by CSMAR. Year fixed effects are based on the year that recommendation revisions are announced. The sample period is 2010-2020. Heteroscedasticity-consistent standard errors are shown in parentheses.

Panel A: Upgrades

	(1)	(2)	(3)	(4)
After revisions × Influential	-0.0192*	-0.0201**	-0.0201**	-0.0201**
	(0.01)	(0.0095)	(0.0086)	(0.0086)
After revisions	-0.0051*	-0.0052*	-0.0052*	-0.0052*
	(0.0031)	(0.0029)	(0.0027)	(0.0027)
Influential	0.0181**	0.0246***	0.0252***	0.0253***
	(0.0071)	(0.0068)	(0.0061)	(0.0061)
Size		0.0180***	0.0282***	0.0281***
		(0.0014)	(0.0014)	(0.0015)
Turnover rate		0.0428***	0.0196***	0.0191***
		(0.0034)	(0.0032)	(0.0033)
Past return		-0.1760***	-0.1781***	-0.1799***
		(0.0084)	(0.0079)	(0.008)
BM ratio		0.1761***	0.1639***	0.1635***
		(0.0051)	(0.0048)	(0.0049)
ROE		0.1733***	0.0815***	0.0851***
		(0.021)	(0.0192)	(0.0193)
STDDEV		1.7215***	1.1717***	1.1403***
		(0.1874)	(0.236)	(0.237)
Ln(Analyst coverage)		0.0269***	0.0093***	0.0098***
		(0.0021)	(0.002)	(0.002)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	19,016	18,126	18,126	18,126
*R*2	0.001	0.133	0.289	0.295

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

Panel B: Downgrades

	(1)	(2)	(3)	(4)
After revisions × Influential	0.0310***	0.0297***	0.0297***	0.0297***
	(0.01)	(0.0092)	(0.0083)	(0.0083)
After revisions	-0.0094**	-0.0105***	-0.0105***	-0.0105***
	(0.0042)	(0.0039)	(0.0035)	(0.0035)
Influential	-0.0228***	-0.0336***	-0.0064	-0.0061
	(0.0071)	(0.0066)	(0.0069)	(0.007)
Size		0.0172***	0.0267***	0.0257***
		(0.0017)	(0.0017)	(0.0018)
Turnover rate		0.0035	-0.0057	-0.0063
		(0.004)	(0.0039)	(0.0039)
Past return		-0.2369***	-0.1999***	-0.1950***
		(0.0102)	(0.0097)	(0.0098)
BM ratio		0.1902***	0.1844***	0.1816***
		(0.0061)	(0.0057)	(0.0058)
ROE		0.1924***	0.1020***	0.1022***
		(0.0257)	(0.0233)	(0.0235)
STDDEV		1.6712***	1.7264***	1.6154***
		(0.2547)	(0.306)	(0.308)
Ln(Analyst coverage)		0.0224***	0.0067**	0.0071***
		(0.0029)	(0.0027)	(0.0027)
Broker FE	No	No	No	Yes
Year FE	No	No	Yes	Yes
N	12,630	12,214	12,214	12,214
$R2$	0.001	0.173	0.335	0.346

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

Chapter 5. Conclusion and recommendations for future work

Sell-side analysts play important roles in the financial markets, especially in the process of information production and transmission. In this thesis, I focus on how sell-side analysts affect the information environment of stock market and characteristics that determine the performance and market influence of these analysts.

I first examine how MiIFD II (Markets in Financial Instruments Directive II), an updated financial regulation implemented in European Union in early 2018 changed the aggregate level of price informativeness of stock market through changing the incentives of sell-side analysts. My research shows that although total number of sell-side analysts decreased after the implementation of MiFID II, they worked harder to provide higher amount of firm-specific information to the stock market and increased the overall price informativeness of European stock market.

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

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

Another finding of this study that has important implications is that the asymmetricity of the reduction in stock return synchronicity. The fact that stock return synchronicity decreases more for negative returns suggest that analyst-generated firm specific information is more important for negative stock returns. While this is somewhat intuitive, partly because the management is more incentivized to make sure positive information is incorporated, it also implies that stock prices become less contagious to negative shocks and reduce the negative systematic risk component in stock returns.

Finally, from a regulatory perspective, the results of this study suggest that MiFID II achieves a better information environment with fewer analysts producing the information. It also shows 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.

This research has some important limitations too. It focuses on relatively shorter period of time around the introduction of MiFID II to minimize the chance of capturing changes driven by other events, such as the European financial crisis and COVID-19 pandemic. It is possible that some of the effects change over time, so the longer-term implications remain a subject for future research. Another important factor to consider is that some of our US control firms might be also affected by MiFID II, as some brokers may choose to follow global policies for equity research.

Then I go on to study how seniority determines the performance of sell-side analysts, separately for analyst teams and individual analysts that work alone. My research shows that seniority serves as important factors in determining the overall performance of analyst teams but matters less in determining the performance of individual analysts that work by themselves. It seems seniority of analyst is a valuable attribute only when analysts work together.

In some additional analyses, I further enhance the validity of my main results by using team-changes of sell-side analysts as opportunities to study the role of senior analysts within an existing analyst team. Within the team-change sample, I directly examine how senior analysts could affect the forecast accuracy of an existing analyst team covering the same listed firm. I examine the change in PMAFE, the relative forecast accuracy measure, to compare the before and after team-change relative performance of an analyst team against its peers covering the same listed firm. Comparing the PMAFE instead of absolute forecast error is intended to make sure forecast accuracy is comparable before and after the team-change event. By exploring the relationship between seniority and PMAFE in team-change subsample, I find evidence to show senior analysts could significantly improve the relative forecast accuracy of an existing analyst team. This study shows seniority of sell-side analysts is an important determining factor of analyst teams' overall performance. However, seniority seems to matter less when analysts work alone by themselves.

Finally, I examine the relationship between synchronicity and price informativeness. Recommendation revisions issued by sell-side analysts contains firm-specific information, posing a valuable opportunity to directly examine the relationship between synchronicity and price informativeness. I find that synchronicity between individual stock returns and market returns decreases after recommendation revisions, suggesting a negative relationship between synchronicity and price informativeness. This result supports the theory of Roll (1988) and many studies based on such theory, including Piotroski and Roulstone (2004) and Crawford, Roulstone, and So (2012) just to name a few.

In additional analyses, I examine the continuous change in R-squared values 80 trading days both before and after recommendation revisions to observe the change of price informativeness on daily basis. I find that synchronicity in general starts to decrease as early as 15 trading days before the actual recommendation revision announcement days. This result indicates that that potential leak of valuable information on average starts as early as 15 trading days ahead of actual recommendation revision announcements, supporting the theory of Christophe et al. (2010) and many others.

In terms of recommendations for future work, I have the following suggestions regarding the roles of sell-side analysts in the financial markets. First, whether the role of star analysts could partially explain the results introduced in Chapter 3 of this thesis needs better exploration. Second, the detailed process of information production and transmission by sell-side analysts seems under-explored now, especially the information transmission process between sell-side analysts and their buy-side institutional clients. How the information is transmitted to buy-side analysts and how the information is verified, evaluated, and eventually contribute to the investment decision making process of portfolio managers are left roughly under-explored. This is, of course, largely due to the fact that datasets regarding decision making process within buy-side institutions, especially regarding buy-side analysts, are not easily available. Third, the behavioral biases of sell-side analysts are also interesting topics to explore as far as I’m concerned, especially the over-confidence bias and recognition bias of young star analysts who became famous and successful in very early stage of their career. Sell-side analysts join the industry in quite younger age, usually right after completing their master's degrees or MBAs especially in Chinese market in their 20s. This means that at least some of the sell-side analysts could become rich and famous at very early stage of their career after winning one or two awards together with their analyst teams, which usually led by senior analysts. Forecasts and recommendations issued by such young star analysts could potentially be affected by recognition biases and emotional biases. Last but not least, buy-side analysts are also interesting market participants to explore in general. Although conducting research focusing on buy-side analysts would require extensive amount of work to acquire data from buy-side analysts since their activities and information are not always publicly available.