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Research unbundling and market liquidity: Evidence from MiFID II

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Abstract

The second Markets in Financial Instruments Directive (MiFID II) mandated the unbundling of payments for research and trading. This research explores whether the impact of MiFID II differs between large and small firms in terms of analyst coverage and stock liquidity. Focusing on the UK stock markets we find a significant drop in analyst coverage on the Main Market, which leads to a deterioration in market liquidity. In contrast, the requirement of AIM firms to retain a Nominated Adviser, who often provides research coverage, has mitigated the impact of MiFID II.

KEYWORDS

analyst coverage, MiFID II, stock liquidity, unbundling

JEL CLASSIFICATION

D53, D82, G18

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1 | INTRODUCTION

Analyst research plays a key role in producing and disseminating information in financial markets. In January 2018, the European Union (EU) introduced the second Markets in Financial Instruments Directive (MiFID II), which requires asset managers to pay for research separately from trade execution services. Before MiFID II, analyst research was, in general, not paid for separately but was provided as part of the bundle of services from sell-side brokers (known as 'soft dollars') and the costs of this were passed onto investors. The unbundling requirement was intended to improve market transparency, reduce excessive production of research by brokerage houses (the 'sell-side') and thereby reduce costs for investors. The implementation of MiFID II has significantly changed the market for research: the majority of asset managers decided to absorb the cost of research themselves and accordingly the demand for sell-side research reduced. As a result, brokerage houses scaled back the amount of analyst research they supplied. This paper analyses the implications of these changes for market liquidity and firm idiosyncratic liquidity.

Efficient information production is essential for financial markets (Campbel & Kracaw, 1980) and sell-side analysts are significant contributors to the flow of information between firms and investors (Bradshaw et al., 2017). Brennan and Subrahmanyam (1995) show that greater analyst coverage tends to reduce adverse selection and results in higher market depth. Analyst coverage provides numerous economic benefits for firms through enhanced visibility (Merton, 1987) and reduced agency costs (Lang et al., 2004; Moyer et al., 1989) that ultimately enhance market liquidity (Irvine, 2003). From the public information perspective, analyst research promotes market liquidity by reducing information asymmetry (Barth & Hutton, 2004; Claessens et al., 2002; Coller & Yohn, 1997; Easley et al., 1998; Frenkel et al., 2020; Roulstone, 2003). From the information disclosure perspective, analysts may discover and publish information that would otherwise remain private (Charitou et al., 2019). The mandatory separation of payments for investment research and trade execution, therefore, could have a detrimental effect on information production and stock liquidity.

Guo and Mota (2021) investigate the impact of MiFID II and show that it led to a significant reduction in the quantity of sell-side analyst coverage, particularly for large firms, but that the quality of the remaining research was improved. In addition, Fang et al. (2020) and Lang et al. (2021) provide evidence that stock-market liquidity decreased post-MiFID II. In this paper, we examine the aggregate market impact of MiFID II, focusing on firm liquidity and paying particular attention to the impact on small and medium-sized enterprises (SMEs) since the impact of unbundling on SMEs might be expected to be particularly negative, given that analyst coverage of many SME stocks was limited even before MiFID II was implemented. In a recent QCA/Peel Hunt Mid and Small-Cap survey,[1] 70% of institutional investors report a negative impact of MiFID II on UK-listed SMEs, and 78% expressed support for exempting SMEs from unbundling requirements. Such concerns have led both UK and EU regulators, to consider relaxing the rules regarding unbundling. We explore the evidence that such concerns are justified.

Although MiFID II applied to all EU countries, we focus on the UK (no longer part of the EU since 31 January 2020) where SMEs have a choice of listing venues with differing

[1]QCA/Peel Hunt Mid and Small-Cap Survey, 2021: https://www.peelhunt.com/insights/qca_peelhunt_ survey2021.

institutional arrangements.[2] Companies can choose which market segment to list on. Most large companies are listed on the LSE Main Market, which is regulated by the UK Listing Authority. However, as in many European countries, the UK also has a less regulated market—AIM—which is the venue for many, though not all, SMEs.[3] An important feature of AIM regulation is that companies must retain a corporate advisor, known as a Nominated Adviser (NOMAD).[4] These NOMADs will often also act as brokers and provide analyst coverage, although in some cases NOMADs do not provide broking services. We explore whether this requirement mitigates the shrinking research coverage driven by MiFID II unbundling. SMEs listed on the Main Market are exempted from the NOMAD rule, which allows us to compare the impact of market regulation on analyst information production and on market liquidity.

Our primary empirical analysis compares market reactions of firms listed on the LSE Main Market to those on AIM over the period from 2015 through 2020, which is 3 years before and after MiFID II.[5] We combine information from IBES, Compustat, Datastream, and the LSE. Our results suggest that MiFID II is associated with a significant reduction in analyst coverage on the Main Market, in line with earlier analysis performed at the EU level. Average analyst coverage reduced by around 12% after MiFID II, falling from 9.1 analysts per company to 8.0. However, research coverage of AIM companies increased slightly by 6.3%, albeit from a much lower level of around 1.5 analysts per company. Analyst forecast quality increased marginally for Main Market companies but improved significantly for AIM companies in the post-MiFID II period.

We consider two economic forces fostering this divergence. First, we present evidence that, as the demand for large-cap research fell, there was a flow of analysts to the less-populated SME market. Second, we conjecture that the close on-going relationship between the NOMAD and the company may enable a strengthened information channel, in particular when the NOMAD also acts as the broker and provides analyst coverage.

These different market reactions to MiFID II between AIM and the Main Market allow us to identify the extent to which stock liquidity is driven by weakened information production associated with the unbundling rule of MiFID II. If an increase in analyst coverage promotes public information, a significant drop in analyst coverage on the Main Market will lead to a deterioration in market liquidity. This is what we find on the Main Market. In contrast, for the AIM market after the execution of MiFID II, the marginally higher coverage and the improved quality of forecasts are associated with improved liquidity. Further, when a brokerage house stops covering a company that they used to cover before the regulation, stock liquidity of the company accordingly falls. Conversely, when an AIM company has equity research issued by

[2]According to Financial Conduct Authority (FCA), SMEs are defined as firms with a market cap below £200 m since the research coverage below this is at its lowest. See FCA consulting paper on 'Changes to UK MiFID's Conduct and Organizational Requirements', 2021: https://www.fca.org.uk/publication/consultation/cp21-9.pdf.

[3]Within Europe such less-regulated segments are referred to as exchange-regulated markets. The London Stock Exchange (LSE) set up the Alternative Investment Market in 1995, and it now has more public companies than the main regulated market.

[4]According to AIM rule 26, it is compulsory for AIM firms to appoint and retain at least one corporate advisor (NOMAD) and one broker in an ongoing basis. All AIM-listed firms are required to disclose and update their NOMADs and brokers on their websites, and so we are able to link NOMADs and brokerage houses with the I/B/E/S recommendation file.

[5]In the robustness check, we also test the sample period of 2016–2019, 2 years before and after MiFID II, to investigate the short-term effect of MiFID II. The results remain robust and are presented in the Supporting Information: Table OA2.

its NOMADs, stock liquidity improves. Serving as a firm's NOMAD could provide the brokerage house with additional information through a closer relationship with management, enabling the analyst to issue better quality research. This strengthened information channel through the NOMAD relationship results in better liquidity. Taken together, our findings on research coverage and stock liquidity suggest that strong analyst coverage is associated with better stock liquidity due to reduced information asymmetry.

To further understand the relation between information and liquidity we investigate whether analyst following increases market-wide information or firm-specific information. Prior work suggests that analyst coverage lessens the amount of firm-specific noise (Chan & Hameed, 2006; Liu, 2011). Doukas et al. (2008) show that high analyst coverage creates favourable market conditions by reducing information asymmetry. Ang et al. (2009); George and Hwang (2013) provide evidence that firm idiosyncratic volatility is negatively associated with analyst coverage. In this paper, we decompose liquidity into the systematic and idiosyncratic components and investigate the role of analyst coverage on each. If analysts tend to produce firm-specific information, then unbundling would be expected to impact more on firm idiosyncratic liquidity. Our results suggest that firm idiosyncratic liquidity drops together with analyst coverage on the Main Market post-MiFID II. However, on AIM, both analyst coverage and firm idiosyncratic liquidity are actually enhanced. The results are in line with high analyst coverage being associated with better firm idiosyncratic liquidity due to enhanced dissemination of firm-specific information.

Our paper contributes to the literature in a number of ways. First, we investigate the aggregate market impact of unbundling on market liquidity. Comparing firm-level and analyst-level performance in the pre- and post-regulation period (2014–2019) between US and EU market, Guo and Mota (2021) find a drop in analyst coverage and an improvement in forecast quality after the unbundling, leaving open the question of the aggregate market impact of MiFID II. Previous studies on the influence of unbundling on stock liquidity report divergent empirical results. Anselmi and Petrella find no impact on liquidity but Fang et al. (2020) conclude that liquidity deteriorates following MiFID II. Our study fills this gap by investigating the aggregate market impact of unbundling on market liquidity, particularly for smaller companies where the potential impact is larger. Second, we explore how stock market regulations interact with the unbundling rules within a single country. We show that unbundling has resulted in a much stronger negative impact on information quantity on the LSE Main Market, both for large caps and SMEs. In contrast, and surprisingly, both analyst coverage and research quality improve post-MiFID II on AIM. Third, these different market responses between the Main Market and AIM offer an opportunity to investigate the relation between information and liquidity. If an increase in analyst coverage promotes public information, it will consequently enhance market liquidity. Our results demonstrate that stock liquidity—as measured by liquidity tightness, depth and resilience—deteriorates on the Main Market, especially for SMEs, while it is enhanced for AIM stocks after MiFID II. The results indicate that analyst coverage improves public information and high analyst coverage promotes market liquidity by reducing information asymmetry. We further demonstrate that analyst coverage improves firm idiosyncratic liquidity by enhancing the dissemination of firm-specific information.

The paper proceeds as follows: in Section 2, we introduce the institutional setting and the data. In Sections 3 and 4, we present our empirical evidence on the impact of unbundling on analyst-following and how it facilitates market liquidity. Section 5 concludes.

2 | INSTITUTIONAL BACKGROUND AND DATA

2.1 | Key features of UK market regulation

Research unbundling has fundamentally changed brokers' business models. Traditionally, equity research was bundled within advisors' execution, trading, and other advisory services. However, MiFID II requires separate charges for transactions and research. A recent report from the UK financial regulator, the Financial Conduct Authority (FCA), documents a decline of about 20%–30% in equity research budgets following MiFID II.[6] Since most brokerage houses absorb the research cost directly rather than passing them on to clients, they are forced to thin-out the duplication of research and to decide which they want to pay for. In other words, the new rules reinforce competition between different research houses. Large multiservice brokers may be more effective in distributing their research by setting low fees and/or internally cross-subsidizing their research. If most research is produced by a smaller number of large brokers, this could negatively affect the market information environment, disproportionately impacting firms with different market cap, institutional holdings, or listed exchange. One of the MiFID II surveys from the CFA institute mentions that 54% of participants said they had seen a reduction in analyst coverage, especially for SMEs.[7] MiFID II is anticipated to backpedal these SMEs' research coverage, quality and, therefore, market liquidity. In February 2019, the FCA further discussed MiFID II at the European Independent Research Providers Association.[8] One of the significant tweaks is allowing the paid-for research circulated free of charge,[9] bringing anticipation that issuer-sponsored research will have a higher impact in the market. As discussed earlier, brokers may bias their coverage on firms with potential higher revenue, causing coverage for those SMEs to drop and the dissemination of accurate and robust company information to be severely limited. However, the NOMAD model prevailing on the LSE AIM market could complement the research coverage gap driven by unbundling. The AIM community provides a network of experienced advisors to support companies from the first time they consider a flotation. NOMADs are a special feature of AIM and the retention of a NOMAD by each AIM firm is mandatory.[10] An AIM company may appoint the same firm as both NOMAD and corporate broker to perform the two functions. According to our data, 75.6% of AIM-listed companies decide to appoint the same advisor as both NOMAD and broker.

[6]See 'Changes to UK MIFID's Conduct and Organisational Requirements': https://www.fca.org.uk/publications/consultation-papers/cp21-9-changes-uk-mifid-conduct-organisational-requirements.

[7]See 'MIFID II: 1 Year On' CFA Institute, 2019: https://www.cfainstitute.org/-/media/documents/survey/cfa-mifid-II-survey-report.ashx.

[8]See the keynote speech on 'MiFID II at the European Independent Research Providers Association' by Andrew Bailey on 25 February 2019: https://www.fca.org.uk/news/speeches/andrew-bailey-keynote-speech-mifid-ii-european-independent-research-providers-association.

[9]According to Mola et al. (2013), there are three categories of advisors issuing equity research. (1) Investment bank; (2) independent broker, if analysts' employer has no investment banking affiliation but provides research that is tied to brokerage services and/or institutional trading; (3) paid-for research firm, if analysts' employer provides research that is directly or indirectly paid by covered firms.

[10]The responsibilities of NOMADs and corporate brokers are different. NOMADs assist AIM firms through the admission process and are responsible to the LSE for assessing the appropriateness of AIM firms. Once the firms have been admitted to AIM, these NOMADs continue to provide advice and guidance on all aspects of the AIM rules. On the other side, brokers are securities houses and are responsible for any initial fundraising at flotation and for bringing together buyers and sellers to encourage trading in shares.

Moreover, these NOMADs and brokers often have their own institutional research teams producing research fundamental to ongoing communication with the market.

While firms listed on the LSE Main Market often retain a corporate adviser—referred to in the UK as a corporate broker—their main role is different. In particular, a corporate broker's main role is to act as a point of contact for investors and to provide advice to the company on market conditions and regulatory requirements. Retaining such an advisor is common but not required. An important question we explore is whether the NOMAD system mitigates the negative impact of MiFID II on research coverage, by comparing the experience of SMEs on the Main Market and AIM.

2.2 | Sample construction

Our data set combines information from four main sources: COMPUSTAT, Refinitiv DataStream, Institutional Brokers Estimate System (IBES) and the LSE website. Our sample spans the period 2015–2020, that is, 3 years before and after the regulation, to have a balanced evaluation. In a robustness check, we also test the sample period 2016–2019, 2 years before and after MiFID II, to investigate the short-term effect of MiFID II (the results remain robust). From Refinitiv DataStream, we collect firm-daily stock performance data for all LSE firms and estimate alternative measures of monthly stock liquidity. From the I/B/E/S tape, we gather analysts' characteristics. Since DataStream and IBES are both provided by Refinitiv, we can merge the firm-level data using a unique IBES ticker.

Annual balance sheet information comes from COMPUSTAT. This is merged with the master data set using the unique International Security ID (ISIN). We manually collected the information for NOMADs and brokers from LSE and AIM company websites. Since IPOs and delistings will mechanically affect analyst coverage, we restrict our sample to firms that have valid fundamental and price information continuously from 2015 to 2020. We exclude financial firms and firms that switched market segments during the sample period. Our final sample contains 1132 firms with 567 listed on the LSE Main and 565 listed on AIM.

2.3 | Overview of sample

Table 1 presents summary statistics for the key variables in our sample. To mitigate the effects of outliers, we winsorize all variables at the 1% level. Panel A of Table 1 reports summary statistics for the subsample of firms listing on LSE Main Market and Panel B reports summary statistics for the AIM market.

(a) Analyst Forecasts

Following Hong and Kacperczyk (2010), analyst coverage (*Coverage*) is firm-annual data and is computed as the number of unique analyst (analyst code) who contribute at least one earnings per share (EPS) forecast for a firm within a fiscal year from the IBES detail files. Analyst forecast error (*Forecast_Error*) is the absolute distance between the firms' actual annual EPS and the mean of the analyst forecast within each fiscal year. Analyst forecast dispersion (*Forecast_Dispersion*) is defined as the standard deviation of all the forecasts for a certain firm in a given fiscal year. Given that the values of EPS reported by IBES tend to suffer from data errors, we follow the literature and use EPS from COMPUSTAT (Hong &

TABLE 1 Summary statistics.

This table reports the summary statistics of the key variables in the sample period of January 2015–December 2020. Panel A shows summary statistics for the subsample of firms listing on the LSE Main market. Panel B shows summary statistics for the subsample of firms listing on AIM. Columns (i) present the mean and the standard deviation of all variables in the pre-MiFID II period. Columns (ii) are the mean and the standard deviation of all variables in the postregulation period. Columns (i)–(ii) show the difference in mean values between the two period (pre–post) and the *p*-values of the *t*-statistic test for these pre and post-differences. Summary statistics of analyst characteristics, firm's fundamental features, and the market liquidity measures, and presented. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: LSE main market						
	Pre-MIFID II (i)		**Post-MIFID II (ii)**		**Difference (i)–(ii)**	
	Mean	**SD**	**Mean**	**SD**	**Diff.**	***t*-Value**
Analyst coverage and forecast quality (annual) coverage	9.576	8.766	8.389	7.259	1.186***	(4.176)
Dispersion (%)	0.398	1.437	0.443	1.295	−0.046	(−0.828)
Forecast error (%)	0.314	1.168	0.245	0.865	0.068***	(5.369)
Firm characteristics (annual) Size (mil. GBP)	442.766	1046.998	419.835	980.206	22.932*	(2.198)
BM	0.160	0.594	0.174	0.622	−0.014*	(−2.025)
ROA (%)	0.000	0.309	−0.013	0.298	0.013***	(4.021)
Volatility (%)	1.789	1.545	2.317	2.059	−0.528***	(−29.255)
Stock liquidity (monthly) R spread	0.329	0.691	0.400	0.782	−0.070***	(−9.343)
Amihud	0.184	0.724	0.199	0.740	−0.015*	(−2.009)
Roll	0.650	0.619	0.848	0.814	−0.198***	(−26.772)
Number of firms	567		567			
Number of firms with 0 coverage	129		141			
Number of observations	20,412		20,387			

Panel B: LSE AIM						
	Pre-MIFID II (i)		**Post-MIFID II (ii)**		**Difference (i)–(ii)**	
	Mean	**SD**	**Mean**	**SD**	**Diff.**	***t*-Value**
Analyst coverage and forecast quality (annual) coverage	1.461	2.103	1.553	2.248	−0.092***	(−4.274)
Dispersion (%)	0.751	1.769	0.600	1.440	0.151	(1.624)
Forecast error (%)	0.275	1.014	0.188	0.772	0.088***	(5.376)
Firm characteristics (annual) Size (mil. GBP)	42.879	235.576	25.122	99.731	17.756***	(9.669)
BM	0.021	0.113	0.026	0.163	−0.004*	(−2.536)

(Continues)

TABLE 1 (Continued)

Panel B: LSE AIM	Pre-MIFID II (i)		Post-MIFID II (ii)		Difference (i)–(ii)	
	Mean	**SD**	**Mean**	**SD**	**Diff.**	***t*-Value**
ROA (%)	−0.192	0.548	−0.178	0.496	−0.014*	(−2.510)
Volatility (%)	3.035	2.501	3.407	2.638	−0.372***	(−14.574)
Stock liquidity (monthly) R Spread	0.741	0.677	0.709	0.564	0.031***	(5.071)
Amihud	0.367	0.865	0.289	0.694	0.078***	(9.918)
Roll	1.086	1.057	1.212	1.097	−0.126***	(−11.272)
Number of firms	565		565			
Number of firms with 0 coverage	289		297			
Number of observations	20,340		20,328			

Kacperczyk, 2010). We scale the forecast error and forecast dispersion by each firm's previous year-mean stock price to mitigate heteroskedasticity concerns (Hong & Kacperczyk, 2010). Following Guo and Mota (2021), we construct two samples for firm-level analysis, one for quantity and another for quality. The sample for quantity captures the coverage change, so the firm's coverage should be larger than or equal to zero. As the forecast quality requires at least two forecast records, when estimating forecast quality we restrict attention to firms with at least two different analysts providing research coverage during the fiscal year.

The summary statistics in Table 1 demonstrate a significant drop in coverage following the introduction of MiFID II on the Main Market. Specifically, analyst coverage reduced by an average of 12.4%, falling from 9.58 analysts per company to 8.39, with a highly significant difference ($p < 0.01$). In contrast, research coverage of AIM companies increased by 6.3% from 1.46 analysts per company to 1.55, a change that is also statistically significant ($p < 0.01$). These results suggest a reallocation of broker research resources from the well-researched Main Market towards AIM. To explore this reallocation further, in Figure 1 we present a Sankey chart that tracks analyst head counts across market segments and their movement from 2015 to 2020. As noted earlier, unbundling has reduced brokerage house revenue to cover the cost of research production, which is likely to result in pared-down analyst numbers, merging of teams and, possibly, reduced analyst seniority. Accordingly, the total head counts of analysts covering the Main Market has reduced since MiFID II and this reduction is most pronounced for big-cap firms on the Main Market. The Sankey chart shows a strong movement of analysts from LSE Main to AIM post-MiFID II. From 2018 to 2020, 173 analysts moved from LSE Main Market to AIM. The upstream flow from AIM to the Main Market is much weaker: 76 analysts in total from 2018 to 2020. Nevertheless, while some analysts re-positioned themselves in this way, it is noticeable that overall analyst numbers have fallen by about 20% over our sample period.

These trends are consistent with the interpretation that unbundling enhances analyst competition and results in a switch of analysts to provide coverage on firms with lower competition and higher marginal information. It is noticeable, however, that the gains in

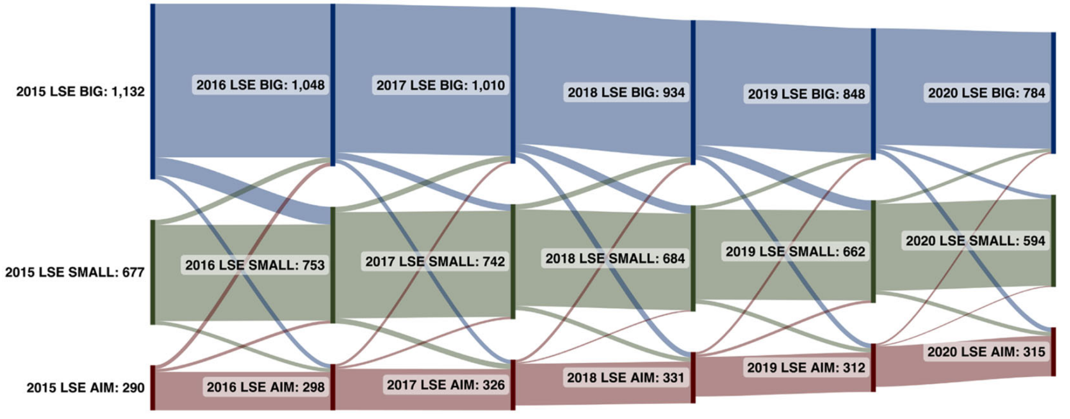

FIGURE 1 Analyst movements between market sectors. This figure presents a Sankey Chart on the analyst headcounts and analyst movement between different market sectors of LSE large-caps, LSE small-caps and AIM from 2015 to 2020. We obtain the analysts forecast data from the IBES Detail History file, then merge their covered firms with market sectors. The total headcounts of analyst cover the Main Market has reduced since MiFID II and this reduction is more pronounced for large-cap firms on the Main Market. The Sankey chart shows a strong trend of analyst movement from LSE Main to AIM after MiFID II. [Color figure can be viewed at wileyonlinelibrary.com]

coverage for SMEs are confined to AIM companies. The number of analysts covering SMEs on the Main Market fell significantly over our sample period. In our sample period, 161 NOMADs advise 565 AIM firms and 115 NOMADS (71%) issued equity research for their covered firms during their advisory period. Figure 2 provides a similar Sankey chart at the level of the broker (rather than the company) and confirms that the number of analysts employed in NOMADs remains constant during the sample periods while non-NOMAD brokers are losing analysts, especially in the post-MiFID II period.

(b) Firm-Specific Characteristics

Table 1 also presents summary statistics on firm-specific characteristics which we include as controls in our regression analysis. These are defined in detail in Supporting Information: Table OA1. They include firm size (*Size*); book-to-market ratio (*BM*), as a proxy for growth opportunities; profitability, as measured by return on assets (*ROA*); excess monthly stock returns (*Ret*), and monthly stock return volatility (*V ol_Ret*).

(c) Stock Liquidity

Various measures of liquidity have been employed in the literature to capture different dimensions of trading activities. Goyenko et al. (2009) explored measures that encapsulate trading cost and volume, while Brunnermeier and Pedersen (2009) emphasized liquidity risk and its interaction with market conditions. Kim and Lee (2014) further studied the role of trading frequency in liquidity measurements. For the purposes of this study, we have chosen to focus on three dimensions of liquidity, in line with the nature of our data set and our research objectives. Recognizing concerns among AIM companies about 'stale' prices and infrequent trading, we have limited our sample to include only firms with active trading volume. We employ daily stock return data for these more actively traded firms to estimate monthly liquidity risk. Following Kyle (1985), we measure stock liquidity across three dimensions: tightness, depth and resilience. In line with Hong and Warga (2000), tightness is measured by

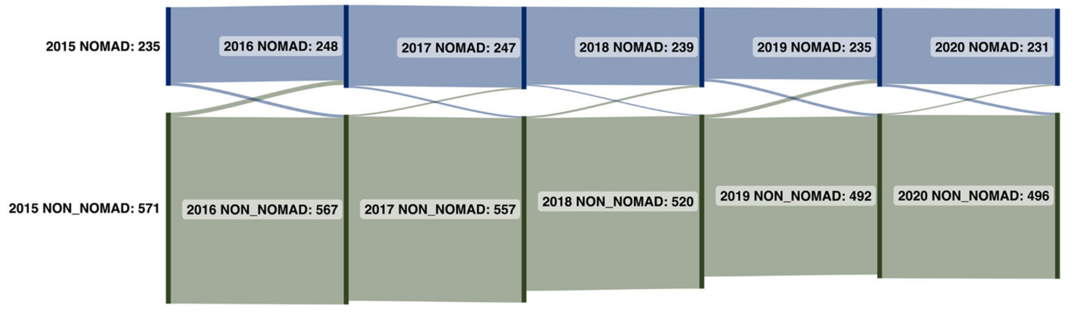

FIGURE 2 Analyst movements between NOMAD and non-NOMAD brokerages. This figure presents a Sankey Chart on the analyst headcounts and analyst movement between different types of brokers from 2015 to 2020. We focus on the subsample of AIM companies to investigate the effect of NOMAD on analyst coverage. We manually collect the information on brokerage type (NOMAD or non-NOMAD). The number of analysts employed by NOMADs has changed only marginally throughout the years, while the non-NOMADS are losing analysts, especially post-MiFID II. [Color figure can be viewed at wileyonlinelibrary.com]

the relative spread (*R_Spread*), which is the quoted spread (the difference between the best ask quote and bid quotes) relative to the mid-price (the average of the best ask quote and bid quotes). R Spread indicates the implicit cost of trading with a smaller R Spread implying higher liquidity:

$$R\ Spread_{it} = \frac{ask_{it} - bid_{it}}{0.5 \times (ask_{it} + bid_{it})}. \tag{1}$$

We compute the Amihud illiquidity indicator (*Amihud*) to measure the depth of a firm's stock liquidity (Amihud, 2002). The Amihud illiquidity ratio measures the elasticity of liquidity, which is calculated as the daily measure of absolute asset returns to trading volume:

$$Amihud_{it} = \frac{|r_{it}|}{dvol_{it}}, \tag{2}$$

where r_{it} is the return of stock i on day t and $dvol_{it}$ is the trading volume for stock i on day t. The number of trading days for month t is D, and the mean level of illiquidity for month d is calculated as follows:

$$illiq_{id} = \frac{1}{D_{id}} * \sum_{t=1}^{D_{id}} \frac{|r_{it}|}{dvol_{it}}. \tag{3}$$

The time dimension of liquidity is commonly referred to as liquidity resilience. We use the Roll (1984) measure as a proxy of liquidity resilience, which estimates the negative autocorrelation produced by bounces between bid and ask quotes. Transaction costs cause negative serial dependence in successive observed market price changes and larger bid-ask bounces lead to higher negative covariance between adjacent price changes. Roll's measure is calculated as the square root of the negative daily autocorrelation of individual stock returns, that is:

$$Roll_{it} = \sqrt{-\mathrm{cov}(r_{it} r_{it-1})}. \tag{4}$$

Table 1 presents summary statistics of these three liquidity measures. The results show that MiFID II has a differential impact across the market segments. Liquidity fell on the LSE Main Market across all three measures: average R spreads increase by 21.2%, Amihud ratios rise by 8.2%, and Roll's measure of resilience falls on average by 30.5%. However, stock liquidity of AIM stocks improved significantly post MiFID II as measured by R spreads and the Amihud ratio. In contrast, resilience fell. However, these are clearly just univariate comparisons over time, and in the next section, we explore the impact of MiFID II on forecast quality and liquidity within a regression framework.

3 | RESEARCH DESIGN AND EMPIRICAL RESULTS

We employ the following regression model to test whether MiFID II had a differential impact on firms according to whether they were on LSE Main market or AIM:

$$Y_{jt} = \beta_1 POST \times AIM_j + \beta_2 X_{jt} + \alpha_j + \alpha_t + \epsilon_{jt}, \tag{5}$$

where the dependent variable will be our coverage and liquidity measures. To further explore the possible heterogeneous response, we split the LSE Main Market into small-cap and large-cap firms. According to the definition of the FCA, SMEs are defined as firms with annual mean market capitalization of less than 200 million GBP (282 million USD).[11] We adopt this cut-off and run Equation (6) to explore whether there is a heterogeneous response between the small- and large-cap market. Our regression model is different from the Difference in Differences (DID) estimation. The DID estimation relies on the parallel trends assumption, which may not be suitable when both AIM and Main Market are subject to MiFID II. Instead, our regression analysis allows for the investigation of the postimpact of MiFID II on the AIM versus Main Market, providing insights into the specific effects and relationships between these variables.

$$Y_{jt} = \beta_1 POST \times large_j + \beta_2 X_{jt} + \alpha_j + \alpha_t + \epsilon_{jt}. \tag{6}$$

3.1 | The impact of MiFID II on analyst performance

We first investigate the impact of unbundling on analyst performance by estimating Equation (5) with analyst coverage as the dependent variable. Recall that Coverage is computed using firm-annual data and is defined as the number of analysts who provide at least one EPS forecast for that firm within each fiscal year. *POST* is a dummy taking the value one if the year is 2018 or later. X_{jt} is a set of firm and country-level control variables, including *SIZE*, *BM*, *Ret*, *ROA* and *Vol_Ret*. We further construct two measures for analyst forecast quality: forecast error and forecast dispersion. Analyst forecast error (*Forecast_Error*) is the absolute distance between a firms' actual annual earnings per share and the mean of the analyst forecast within each fiscal

[11]The definition of SMEs in United Kingdom, see: https://www.fca.org.uk/publication/consultation/cp21-9.pdf.

year. Analyst forecast dispersion (*Forecast_Dispersion*) is defined as the standard deviation of all the forecasts for a certain firm in a given fiscal year. Both the forecast error and forecast dispersion are scaled by the firm's previous year mean stock price to mitigate the heteroskedasticity concerns (Hong & Kacperczyk, 2010)[12] Standard errors are double-clustered by firm and year to account for any remaining heteroscedasticity.

Private Equity (PE) and Venture Capital (VC)-backed companies may exhibit enhanced coverage and performance on both the Main and AIM markets compared to their non-backed counterparts (Jelic et al., 2021; Jenkinson et al., 2022). This divergence in coverage adds a complex dimension to the analysis that requires careful examination. Further, foreign firms may demonstrate distinct patterns in information dissemination and liquidity. These differences could stem from various factors such as regulatory environments, market practices, or cultural influences that may uniquely shape the behavior of foreign firms in comparison to domestic companies. To address the firm-level unobservable heterogeneity, which includes these subtle but substantial differences between PE/VC-backed, foreign, and other firms, the analysis includes firm-fixed effects. This statistical approach serves to absorb time-invariant firm heterogeneity, thereby isolating the distinct influences of these different firm categories.[13]

The regression results are reported in Table 2. Columns (1)–(3) report the results for the full sample, including all Main Market and AIM companies. Since there is a significant difference in the economic incentives to provide research coverage between larger companies and SMEs, in columns (4) and (5) we also run the results on our SME subsample. Column (1) includes the POST dummy variable, alongside the controls, to quantify the overall impact of on analyst coverage after MiFID II. This indicates a significant overall drop which translates into a change of −6.6% relative to the mean coverage before the regulation. In column (2) we introduce year-fixed effects, to pick up the impact of the regulatory change, and test whether there is a differential impact on large firms. We find that the impact on analyst coverage is more sizeable, negative, and statistically significant for the large-cap firms, which translates into a drop of 11.2% relative to average coverage before the regulation. In column (3) we find that the coverage of AIM firms increased relative to firms listed on the Main Market in the period after MiFID II. This result suggests strongly that SMEs have had a different experience than large-cap firms.

We are also interested in whether companies on AIM have had a similar experience to similar-sized SMEs list on the Main Market. Column (4) restricts the sample to SMEs and finds no significant reduction in analyst coverage for SMEs after the change in regulation, which is an intriguing result. In column (5) we introduce year-fixed effects and include an AIM dummy variable, which we find to be significantly positive, indicating a noticeably different impact according to which market segment the SMEs are on. Specifically, column (5) of Table 2 shows that coverage for AIM-listed SMEs increased by 46.48% (0.679/1.461) relative to similar-sized firms on the Main Market. This suggests that the details of market regulation are important when assessing the impact of such significant policy changes.

[12]Our results are robust if we further control for the average days between the analyst forecast announcement date and the actual earnings report date (*LN _DIST AN CE*). For brevity, we do not include *LN _DIST AN CE* in this paper. However, it's available upon request.

[13]Institutional holding plays an important role on analyst coverage Firms with higher level of institutional holding may demonstrate higher demand for equity research. As robustness tests, we further control out the institutional ownership in examining the impact of MiFID II on analyst performance. We find consensus results.

TABLE 2 The impact of unbundling on analyst coverage.

This table reports the effect of unbundling on analyst coverage at firm-annual level. The dependent variable is analyst coverage (*Coverage*), which is defined as the number of unique analysts who issue at least one earnings forecast for a particular firm during a fiscal year. *POST* is a dummy variable equal to 1 if the year is larger than 2017. *AIM* is a dummy variable equal to 1 if the firm list on the LSE AIM market. *Large* is a dummy variable equal to 1 if the market capitalisation for an official list larger than 200 million GBP (282 million USD). Columns (1)–(3) report the regression results for the full sample. The regression results for the SME subsample are in columns (4)–(5). All specifications include firm-fixed effects and year-fixed effects. Heteroscedasticity-consistent standard errors, double-clustered by firm and year, are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

	Coverage				
Dependent variables	**Full sample**			**SMEs only**	
Market	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
POST	−0.358**			−0.013	
	(0.103)			(0.062)	
POST × Large		−1.875***			
		(0.385)			
POST × AIM			1.259***		0.679***
			(0.258)		(0.131)
Size	0.289***	0.318***	0.288***	0.258***	0.256***
	(0.069)	(0.074)	(0.069)	(0.039)	(0.038)
BM	−0.763	−0.683	−0.582	−0.485	−0.399
	(0.617)	(0.570)	(0.566)	(0.487)	(0.463)
ROA	0.022	0.033	0.027	−0.015	−0.008
	(0.060)	(0.055)	(0.056)	(0.059)	(0.059)
Ret	−0.189*	−0.287	−0.310	−0.183***	−0.275**
	(0.075)	(0.167)	(0.163)	(0.040)	(0.116)
Volatility	−0.061	−0.027	−0.006	−0.051**	−0.027
	(0.064)	(0.052)	(0.046)	(0.025)	(0.024)
Firm FE	Y	Y	Y	Y	Y
Year FE		Y	Y		Y
Observations	5593	5593	5593	4735	4735
R^2	0.958	0.961	0.960	0.930	0.932

The regressions in Table 2 analyse, in aggregate, analyst coverage before and after MiFID II, but how did this evolve over time? Based on Equation (5), we split the post dummies into year dummies. Figure 3 provides a visual illustration of the significantly different effects of unbundling for each year from 2015 to 2020. The yearly coefficient for the Main market is increasingly negative over time and significant at the 1% level since 2018. While the coefficient

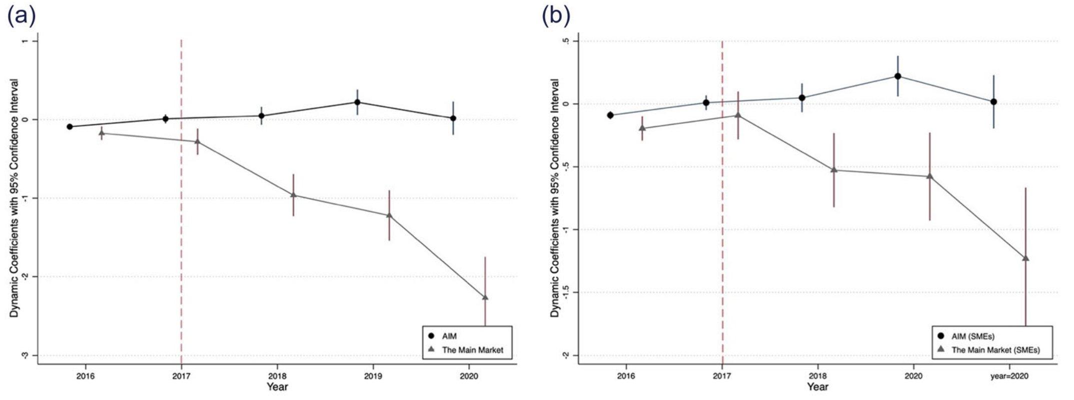

FIGURE 3 The yearly treatment effects of MiFID II. This figure presents the effect of the unbundling on the change of firm-level analyst coverage. To investigate the yearly treatment effect of MiFID II, based on Equation (5), we split the postdummies into year dummies. These figures show the effect of the unbundling on the change of firm-level analyst coverage. Standard errors are clustered at firm and year level. $Y_{jt} = \beta_1 YEAR_t \times AIM_j + \beta_2 X_{jt} + \alpha_j + \epsilon_{jt}$. (a) The yearly coefficient on the coverage change with a 95% confidence interval for the full sample. (b) The yearly coefficient on the coverage change with the 95% confidence interval for the subsample of SMEs. We adjust the value so that both lines start at 0 in 2016. (a) Yearly coefficient plot for the full sample. (b) Yearly coefficient plot for the full sample. [Color figure can be viewed at wileyonlinelibrary.com]

for AIM firms increased slightly from nonsignificant to positive and significant (again at the 1% level) after 2018. Therefore, we conclude that the effects of MiFID II are greater on the Main Market and are persistent and increasing.

Earlier studies by Fang et al. (2020) and Guo and Mota (2021) investigate the impact of MIFID II until the end of 2018 and early 2019 respectively. We also re-run our analysis on a shorter-term window of 2016–2019 (2 years before and 2 years after the MiFID II). We show that the impacts of MiFID II are robust, significant, and long-lasting irrespective of the time period used.[14]

Next we analyse, in Table 3, whether MiFID II had an impact on sell-side analyst forecast quality. Columns (1) and (4) of Panel A in Table 3, for the full sample, show that both forecast error and forecast dispersion decreased after unbundling. The results are in line with Guo and Mota (2021); Fang et al. (2020); Lang et al. (2021). Our focus is more on the heterogeneous impact of MiFID II between large-cap and SME firms, and across market segments. Columns (2) and (5) of Table 3 indicate an insignificant improvement of the forecast quality for large-cap firms on the Main Market. In contrast, the interactive dummy for AIM companies post-MiFID II, included in columns (3), shows a sizeable and significant reduction in forecast dispersion for AIM firms compared with those on the Main Market. The results are consistent with the hypothesis that increased analyst competition associated with unbundling is associated, on average, with improvements in research quality and the effect is more significant for AIM firms.

[14]The regression results on the short-term effect of unbundling are reported in the Supporting Information: Table OA2.

TABLE 3 The impact of MiFID II on sell-side analyst forecast quality.

This table reports the effect of unbundling on the quality of analyst earnings forecasts. Panel A of Table 3 reports the regression results for the full sample and Panel B reports the results for the subsample of SME. The dependent variables are Forecast Error (*Forecast_Error*) and Forecast Dispersion (*Forecast_Dispersion*). *Forecast_Dispersion* is the standard deviation of all the forecasts over all the analysts following the same firm within each calendar year, scaled by the firm's previous year mean price. *Forecast_Error* is the absolute distance between the firm's actual annual earnings per share and the mean of all analyst forecasts within each calendar year, scaled by the firm's previous year mean price. *POST* is a dummy variable equal to 1 if the year is larger than 2017. *AIM* is a dummy variable equal to 1 if the firm list on the LSE AIM market. *Large* is a dummy variable equal to 1 if the market capitalisation for an official list larger than 200 million GBP (282 million USD). All specifications include firm-fixed effects and year-fixed effects. Heteroscedasticity-consistent standard errors are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variables	Forecast dispersion			Forecast error		
	(1)	(2)	(3)	(4)	(5)	(6)
POST	−0.137***			−0.058**		
	(0.033)			(0.026)		
POST × LARGE		−0.042			−0.041	
		(0.031)			(0.026)	
POST × AIM			−0.221***			−0.072
			(0.084)			(0.050)
Size	−0.084	−0.088	−0.077	−0.023	−0.023	−0.021
	(0.062)	(0.063)	(0.063)	(0.051)	(0.051)	(0.051)
BM	0.144	0.095	0.102	−0.372	−0.389	−0.390
	(0.145)	(0.145)	(0.145)	(0.369)	(0.367)	(0.366)
ROA	0.253	0.299	0.279	−0.430***	−0.415***	−0.417***
	(0.201)	(0.203)	(0.203)	(0.126)	(0.125)	(0.125)
Ret	−0.017	−0.078**	−0.059*	0.001	−0.021	−0.019
	(0.036)	(0.034)	(0.032)	(0.032)	(0.029)	(0.030)
Volatility	0.266***	0.255***	0.263***	0.064**	0.059**	0.062**
	(0.047)	(0.046)	(0.047)	(0.030)	(0.030)	(0.030)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE		Y	Y		Y	Y
Observations	3187	3187	3187	3179	3179	3179
R^2	0.764	0.762	0.764	0.599	0.598	0.599

Taken together, the results in Tables 2 and 3 suggest that MiFID II resulted in a drop in analyst coverage for Main Market firms, with the drop being focused on large-cap firms. In contrast, the SMEs listed on AIM on average gained coverage. This is consistent with unbundling enhancing analyst competition and a shift in analysts towards firms with relatively lower competition or higher marginal information value. The AIM rules require the continued engagement of a NOMAD, which will often provide equity research (as we explore later), and this has provided a further brake on any negative impact of unbundling on coverage. On the other side, the decrease in analyst coverage on LSE Main Market potentially reduces the amount of information available. Both Guo and Mota (2021) and Fang et al. (2020) suggest a trade-off between research quantity and quality after MiFID II. Unbundling improves the quality of research at the cost of reducing the quantity of research. However, the existing literature does not give a clear answer of the aggregate impact of MiFID II on financial markets. In the next sections, we explore whether the regulatory change impacted on public information and stock liquidity.

3.2 | The impact of MiFID II on market liquidity

We examine the aggregate impact of unbundling on firm stock liquidity by running Equations (5)–(6) with the three liquidity proxies as dependent variables. Although MiFID II strengthens analyst competition, resulting in an improvement in forecast quality, the decline in analyst coverage, in particular for larger firms, may cause deterioration in the information environment, with increased information asymmetry. This could result in lower firm liquidity. The dependent variables are the three-dimensional liquidity measures for firm j in month t, tightness (*R_spread*), depth (*Amihud*) and resilience (*Roll*). X_{it} is a set of control variables including logarithm of market capitalization (*SIZE*), logarithm of book-to-market ratio (*BM*), market return (proxied by the FTSE index return and presented as R_m), stock return (*Ret*), return on asset (*ROA*). Standard errors double-clustered by firm and year to account for heteroscedasticity. We further include firm fixed effects and, in most specifications, year-fixed effects.

Table 4 reports the results for the aggregate impact of MiFID II on market liquidity with the full sample. Columns (1), (4) and (7) of Table 4 show that, in the overall sample, MiFID II has significantly increased spreads and reduced resilience. Market depth also fell after the change in regulation, but the impact is not statistically significant. In columns (2), (5) and (8) we introduce time dummies to pick up the impact of the regulatory change and include an interactive dummy POST × BIG to test whether there is any differential effect on larger firms. We find positive and significant coefficients when *R_spread* and *Amihud* are the dependent variables, suggesting a deterioration in market liquidity for large-caps after the implementation of MiFID II, although we find no impact on resilience. In contrast, the negative and significant coefficients on *POST × AIM* suggest that stock liquidity of AIM companies improved across all the three liquidity measures. These translate to a change of −11.88%, −24.80% and −3.5% relative to the mean R spread, Amihud, and Roll measures, respectively, for AIM-listed firms post-MiFID II.

Both Fang et al. (2020) and Lang et al. (2021) find suggestive evidence that market liquidity decreases for EU firms following MiFID II, while they do not discuss the impact of unbundling on SME markets. To focus on the impact of unbundling on SMEs and to address the concern whether our results for AIM firms are driven by market capitalisation, in Table 5 we report regression results on the subsample of SMEs only. The results confirm that, although unbundling is associated with a deterioration in stock liquidity, SMEs listed on AIM show better stock liquidities compared with SMEs listed on the Main Market. This result is statistically significant and economically large.

TABLE 4 The impact of unbundling on stock liquidity (full sample).

This table reports the effect of unbundling on market liquidity for the full sample at firm-monthly level. The dependent variables are the three-dimensional liquidity measures: tightness (*R_spread*), resilience (*Roll*) and depth (*Amihud*). All specifications include firm fixed effects and year-fixed effects. Heteroscedasticity-consistent standard errors, are double clustered by firm and year, are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variables	R spread			Amihud			Roll's measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
POST	0.038***			0.010			0.055***		
	(0.009)			(0.010)			(0.010)		
POST × Large		0.020***			0.065***			0.001	
		(0.008)			(0.009)			(0.009)	
POST × AIM			−0.088***			−0.091***			−0.038***
			(0.012)			(0.014)			(0.012)
Size	−0.072***	−0.070***	−0.071***	−0.082***	−0.082***	−0.082***	0.011	0.014*	0.013
	(0.010)	(0.010)	(0.009)	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)	(0.008)
BM	0.042	0.045	0.037	0.007	0.015	0.008	−0.002	−0.006	−0.011
	(0.047)	(0.047)	(0.046)	(0.036)	(0.036)	(0.037)	(0.042)	(0.043)	(0.042)
R_m	−0.010***	−0.011***	−0.011***	−0.062***	−0.062***	−0.062***	−0.007	−0.008	−0.008
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Ret	−0.009***	−0.009***	−0.009***	−0.060***	−0.060***	−0.060***	−0.002	−0.003	−0.003
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
ROA	−0.152***	−0.150***	−0.147***	−0.081**	−0.078**	−0.076**	−0.037**	−0.035**	−0.034*
	(0.028)	(0.028)	(0.027)	(0.032)	(0.032)	(0.031)	(0.018)	(0.018)	(0.018)

(Continues)

TABLE 4 (Continued)

Dependent variables	R spread			Amihud			Roll's measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Volatility	0.023***	0.023***	0.023***	0.054***	0.055***	0.054***	0.223***	0.222***	0.222***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GDP	−0.287**	−0.478***	−0.494***	−0.085	−0.179	−0.189	−1.487***	−1.743***	−1.751***
	(0.113)	(0.108)	(0.109)	(0.140)	(0.155)	(0.155)	(0.169)	(0.189)	(0.189)
Unemployment	0.037***	−0.007	−0.009	0.069***	−0.040**	−0.042**	−0.107***	−0.088***	−0.089***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.018)	(0.018)	(0.015)	(0.019)	(0.019)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE		Y	Y		Y	Y		Y	Y
Observations	63,177	63,177	63,177	63,333	63,333	63,333	60,209	60,209	60209
R^2	0.765	0.766	0.767	0.378	0.380	0.380	0.558	0.559	0.559

TABLE 5 The impact of unbundling on stock liquidity (subsample of SMEs).

This table reports regression results on the impact of unbundling on stock liquidity for the subsample of SMEs. The regressions are at firm-monthly level. The dependent variables are three-dimensional liquidity measures: tightness (*R_spread*), resilience (*Roll*) and depth (*Amihud*). All specifications include firm-fixed effects, and year-fixed effects. Heteroscedasticity-consistent standard errors, double-clustered by firm and year, are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variables	R Spread		Amihud		Roll's measure	
	(1)	(2)	(3)	(4)	(5)	(6)
POST	0.048***		0.015		0.052***	
	(0.011)		(0.012)		(0.012)	
POST × AIM		−0.107***		−0.093***		−0.043***
		(0.014)		(0.016)		(0.013)
Size	−0.080***	−0.078***	−0.095***	−0.094***	0.014*	0.016*
	(0.010)	(0.010)	(0.011)	(0.011)	(0.009)	(0.009)
BM	0.057	0.051	0.015	0.017	−0.012	−0.021
	(0.060)	(0.058)	(0.044)	(0.045)	(0.049)	(0.049)
R_m	−0.011***	−0.012***	−0.067***	−0.067***	−0.008	−0.010
	(0.002)	(0.002)	(0.006)	(0.006)	(0.007)	(0.007)
Ret	−0.010***	−0.010***	−0.065***	−0.064***	−0.004	−0.005
	(0.002)	(0.002)	(0.006)	(0.006)	(0.007)	(0.007)
ROA	−0.151***	−0.147***	−0.079**	−0.074**	−0.034*	−0.031*
	(0.028)	(0.028)	(0.032)	(0.032)	(0.018)	(0.018)
Volatility	0.025***	0.024***	0.057***	0.058***	0.224***	0.223***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
GDP	−0.337**	−0.600***	−0.114	−0.258	−1.508***	−1.833***
	(0.140)	(0.132)	(0.175)	(0.192)	(0.203)	(0.225)
Unemployment	0.045***	−0.010	0.083***	−0.059***	−0.112***	−0.091***
	(0.014)	(0.015)	(0.016)	(0.023)	(0.018)	(0.023)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE		Y		Y		Y
Observations	53,977	53,977	54,114	54,114	51,674	51,674
R^2	0.742	0.744	0.369	0.371	0.554	0.554

The results thus far, in Tables 2–5, demonstrate a clear divergence post-MiFID II for firms listed on AIM and the Main Market with respect to analyst coverage, forecast quality, and stock liquidity. Main market firms experience a significant drop in analyst coverage, a marginal enhancement in quality, and a deterioration of market liquidity. For AIM firms, analyst coverage marginally increases and forecast quality and liquidity improve. Clearly, these effect individually do not shed light on causality, and in the next section, we employ instrumental variables regressions to investigate the extent to which stock liquidity is driven by weakened information production associated with unbundling.

The presence of security analysts can increase both market-wide and firm-specific information (Chan & Hameed, 2006; Piotroski & Roulstone, 2004). We explore this issue by decomposing firm stock liquidity into systematic and idiosyncratic components. If security analysts tend to produce firm-specific information, then the effects of unbundling will be on firms' idiosyncratic liquidity risk. On the other hand, if security analysts tend to produce market-wide information, then the impact of unbundling will be on firms' systematic liquidity risk.

Motivated by Pástor and Stambaugh (2003); Acharya and Pedersen (2005), we employ a time series regression model to decompose the daily variation in individual stock liquidity into systematic and idiosyncratic components. More specifically, we regress the daily firm-level liquidity measures on daily aggregate market liquidity and excess market returns. The monthly idiosyncratic volatility of a stock is the monthly standard deviation of the regression residuals e_{it}. As shown in Equation (7):

$$c_{it} = \alpha_{it} + \beta_{1i} C_{Mt} + \beta_{2i} (R_{it} - r_{ft}) + \epsilon_{it}. \tag{7}$$

C_{Mt} is the aggregate market liquidity on day t. $(R_{it} - r_{ft})$ is the excess market return for stock i on day t, where R_{it} is the log return for stock i on day t and r_{ft} is the log risk-free return (proxied by 3-month t-bills). The idiosyncratic liquidity risk for stock i is the monthly standard deviation of the residual term, $\sigma(\epsilon_{it})$. The systematic liquidity risk for stock β_{2i} represents the covariance of a security's illiquidity to the excess market return.

Since the mean level of liquidity and the standard deviation of the residuals from Equation (7) are highly correlated, for every month, we compute a coefficient of variation by dividing the idiosyncratic volatility of liquidity by the mean level of liquidity:

$$idio\_liq_{im} = \frac{\sigma(\epsilon_{it})_m}{liq_{im}}, \tag{8}$$

where $idio\_liq_{im}$ is firms' idiosyncratic liquidity.

Table 6 presents the results for the impact of MiFID II on market idiosyncratic liquidity risk. Panel A presents the results for the full sample and Panel B focuses on the subsample of SMEs. Columns (1), (3) and (5) of Panel A, Table 6, show a positive relationship between MiFID II and the idiosyncratic liquidity risks of the main large-caps. The coefficients on $POST \times Large$ are positive and significant when the dependent variable is Idio_Amihud, and marginally significant for Idio_R_Spread, which suggests that MiFID II heightens the idiosyncratic liquidity risk for the large caps on the Main Market. We find no significant impact with Roll's measure. Statistically, the annual mean of Idio-R spread increased 11.11% (from 0.036), and the Idio-Roll increased 29.46% (from 1.436) than that of the levels prior unbundling. In contrast, for the AIM market, columns (2) and (4) of Panel A, Table 6, indicate that the idiosyncratic liquidity risk has significantly reduced after MiFID II. The coefficients for $POST \times AIM$ translate to a drop of 6.77% (Idio R spread) and 15.64% (Idio Amihud) relative to their average levels before the regulatory change. We find a negative, but insignificant, impact using Roll's measure (column [6]).

TABLE 6 MiFID II and idiosyncratic liquidity risk.

This table reports the effect of unbundling on the idiosyncratic liquidity risk at firm-monthly level. Panel A of Table 6 reports the regression results for the full sample and Panel B reports the results for the subsample of SME. The dependent variables are *Idio_R_Spread*, *Idio_Amihud* and *Idio_Roll* measure. All specifications include firm-fixed effects and year-fixed effects. Heteroscedasticity-consistent standard errors, are double clustered by firm and year, are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: Full sample						
Dependent varibales	**Idio R Spread**		**Idio Amihud**		**Idio Roll's measure**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
POST × Large	0.003*		0.107***		−0.025	
	(0.002)		(0.025)		(0.029)	
POST × AIM		−0.013***		−0.170***		−0.056
		(0.003)		(0.039)		(0.040)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	63,032	63,032	61,919	61,919	53,828	53,828
R^2	0.654	0.654	0.248	0.248	0.452	0.452

Panel B: Subsample of SMEs			
	Idio R Spread	**Idio Amihud**	**Idio Roll's measure**
Dependent variables	**(1)**	**(2)**	**(3)**
POST × AIM	−0.015*** (0.003)	−0.181*** (0.045)	−0.178*** (0.061)
Controls	Y	Y	Y
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	53,832	52,739	46,180
R^2	0.620	0.241	0.304

Next, in Panel B of Table 6, we report the regression results on the subsample of SMEs only. The negative and significant coefficient of $POST \times AIM$ further confirms that the impact of MiFID II on market idiosyncratic liquidity risk is more beneficial and pronounced for AIM. Overall, for SMEs, unbundling raised the idiosyncratic liquidity risk for the Main Market, in contrast, it reduced the idiosyncratic liquidity risk for AIM. This effect is statistically and economically significant.

Further, we examine the relationship between unbundling and firm systematic liquidity risk. Following Acharya and Pedersen (2005), we take the covariance of a security's liquidity to the excess market return as the proxy for systematic liquidity risk (β_{2i}). The results show no significant relationship between MiFID II and firm-level systematic liquidity risk for either market, confirming our hypothesis that the main impact of unbundling is on firm-specific information rather than market-wide information.[15]

3.3 | Endogeneity?

It should be noted that AIM attracts companies from many different countries and there are consequently disparities in accounting practices and regulatory frameworks. AIM companies are permitted to prepare and present their financial accounts in accordance with a variety of accounting principles, and such nonuniformity in reporting practices could impact on comparisons between companies and market segments. Companies listed on the main market are generally more regulated and have to satisfy the requirements of the UK Listing Authority. We address these issues by including firm-level fixed effects and also employ Propensity Score Matching (PSM). By using PSM, we match AIM companies with similar firms in the main market, effectively reducing the differences in size, reporting quality, and regulatory rules between the two. The predictive probability (propensity score) of listing on AIM is obtained from a probit model. The result confirms that after matching, the two groups are well balanced, with no significant differences in terms of selected matching variables. After obtaining a closely matched sample, we re-estimate Equation (5) based on the newly matched sample in Table 7. As shown, the regression results based on matched sample are in line with our baseline result in Table 2 and Table 3.

4 | THE ROLE OF NOMAD

4.1 | NOMADs, information provision and stock liquidity

The results from Tables 1–7 show a strong divergence between the Main Market and AIM with respect to analyst coverage, forecast accuracy, various measures of stock liquidity, and firm idiosyncratic liquidity. A unique characteristic of AIM is the requirement for firms to retain the services of a NOMAD, who will often provide research coverage and could potentially improve the provision of information. In this section, we focus on the role of NOMADS to investigate the impact of these institutional arrangements on research coverage and stock liquidity.

From our sample, 75.6% of AIM-listed firms appointed the same advisor to serve as both NOMAD and broker and 52.2% have at least one research recommendation issued by their appointed NOMAD. On average, firms with NOMAD research coverage have almost twice the analyst coverage, better forecast quality, and better stock liquidity than that of the remaining AIM firms whose NOMADs do not provide equity research. To evaluate the marginal benefit of NOMAD research, we conduct a subsample analysis on AIM-listed firms. We construct a dummy variable of *NOMAD_Research*, which equals 1 if a firm's NOMAD issues at least one recommendation on the advised firm within a certain fiscal year. Dependent variables are firm-level analyst performance and the liquidity measures.

[15]For brevity, we do not report the table for regression results of unbundling on systematic liquidity. However, it's available upon request.

TABLE 7 The impact of unbundling on analyst coverage and stock liquidity [results based on propensity score matching (PSM)].

This table reports the regression results based on the matched sample through PSM. The sample period covers January 2016 to December 2019. The dependent variables are analyst coverage (*Coverage*) and the three-dimensional liquidity measures: tightness (R-spread), resilience (Roll) and depth (Amihud). POST is a dummy variable equal to 1 if the year is 2018 or later. *AIM* is a dummy variable based on PSM, which is equal to 1 if the firm list on the LSE AIM market. All specifications include firm-fixed effects, and year-fixed effects. Heteroscedasticity-consistent standard errors, double-clustered by firm and year, are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

Dependent Variables	Coverage (1)	R-Spread (2)	Amihud (3)	Roll (4)
POST × AIM	1.212***	−0.041**	−051***	−0.002**
	(0.276)	(0.016)	(0.017)	(0.013)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5589	63,177	63,333	60,209
R^2	0.952	0.752	0.357	0.550

Table 8 presents the impact of NOMAD research on the subsample of AIM-listed firms at firm-monthly level. We report the impact on analyst performance in Panel A of Table 8. The coefficient on *POST × NOMAD_Research* is positive and significant for *Coverage*; this translates to a 11.2% increase in analyst coverage for firms with NOMAD research after MiFID II. Moreover, the coefficients on *POST × NOMAD_Research* are also strongly negative and significant when Forecast Dispersion and Forecast Error are the depended variables. These results suggest a beneficial impact from NOMAD research on the quality of market information, consistent with the hypothesis that the close on-going relationship between companies and their NOMADs enables a strengthened information channel. Equity research issued by the appointed NOMAD may contain more firm-specific information that can improve the quality of information for the covered firms.

Further, we explore whether the analyst coverage from NOMADs has marginal benefits on a firm's liquidity. Panel B of Table 8 reports the regression results. Coefficients on *POST×NOMAD_Research* for all the liquidity measures are significant at 1% level, suggesting a noticeable increase in liquidity for firms with NOMAD_Research after MiFID II.

Serving as a NOMAD for an AIM firm might provide the financial institution with access to additional sensitive information through ongoing supervision. As a result, if NOMADs issue research on their covered firms, it may contain more firm-specific information. Furthermore, the NOMAD's reputation depends, in part, on the performance of the companies they advise, and so this may result in investors having more confidence in equity research produced by NOMADs. This raises the question as to why any AIM company retains a NOMAD that is not capable, or chooses not to, produce research. The results in this section suggest such companies should review their choice of NOMAD.

TABLE 8 Investigating the role of NOMADs.

This table reports the impact of NOMAD equity research on analyst performance and stock liquidity. Panel A of Table 8 reports the impact of unbundling on analyst performance, compares the impact of recommendations from NOMADs on a firm's overall information quality. Analyst coverage is firm-annual level, and the forecast quality is firm-monthly level. The dependent variables are *Coverage*, *Forecast_Error* and *Forecast_Dispersion*. *NOMAD_Research* is a dummy variable equals to 1 if the NOMADs issue at least one recommendation on their advised firm. Panel B of Table 8 presents the impact of recommendations from NOMADs on a firm's liquidity. The dependent variables are the liquidity and idiosyncratic liquidity measures. All specifications include firm fixed effects. Heteroscedasticity-consistent standard errors are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: Analyst performance (nomad research vs. nonnomad research)			
Dependent variables:	**Coverage(1)**	**Forecast dispersion(2)**	**Forecast error(3)**
POST × NOMAD_Research	0.230*** (0.059)	−0.345 (0.288)	−0.038 (0.483)
Controls	Y	Y	Y
Industry FE	Y	Y	Y
Observations	2865	1048	1046
R^2	0.852	0.236	0.495

Panel B: Liquidity measures (NOMAD research vs. non-NOMAD research)						
Dependent variables:	**R spread (1)**	**Amihud (2)**	**Roll (3)**	**Idio Rspread (4)**	**Idio Amihud (5)**	**Idio Roll (6)**
POST × NOMAD_research	−0.098*** (0.008)	−0.064*** (0.011)	−0.058*** (0.012)	−0.018*** (0.002)	−0.083*** (0.028)	−0.140*** (0.040)
Controls	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Observations	32,437	32,381	29,998	32,387	32,013	26,421
R^2	0.303	0.123	0.492	0.399	0.071	0.376

4.2 | Further analysis: The impact of sole research coverage from NOMADs

SMEs can easily lose coverage completely. From our sample, over half of the SMEs have zero or single coverage (62.1% pre-MiFID II and 59.8% post-MiFID II) and this phenomenon is more severe on AIM (86.4% pre-MiFID II and 75.6% post-MiFID II). Prior literature indicates that the market response is positive to analyst initiations, in terms of price impact and market liquidity (Irvine, 2003). It is therefore worthwhile to explore if a sole analyst, particularly following MiFID II, can still bring the same benefits to SMEs. To address the role of sole analyst coverage, we focus on those SMEs (both on AIM and the Main Market) with either no research coverage or sole analyst coverage and investigate the impact sole NOMAD research coverage on company stock liquidity.

Panel A of Table 9 reports the impact of sole analyst research provided by the NOMAD on market liquidity after unbundling. The coefficients on *POST × NOMAD_Research* are negative and strongly significant across all columns, which indicates that sole research coverage provided by the NOMAD can significantly improve stock liquidity on the covered firms.

TABLE 9 Investigating the role of NOMADs: SMEs with zero or sole analyst coverage.

This table reports the marginal contributions from NOMAD research. Panel A of Table 9 presents regression results for a subsample includes SMEs with either no research coverage or only covered by their NOMAD. Panel B of Table 9 presents regression results for a subsample includes SMEs with only one research coverage. All specifications include industry-fixed effects. Heteroscedasticity-consistent standard errors are shown in parentheses. ***, ** and * correspond to statistical significance at the 1%, 5% and 10% level, respectively.

Panel A: SMEs with zero coverage or only covered by their NOMAD						
Dependent variables:	**R spread (1)**	**Amihud (2)**	**Roll (3)**	**Idio Rspread (4)**	**Idio Amihud (5)**	**Idio Roll (6)**
POST × NOMAD_research	−0.282***	−0.190***	−0.067***	−0.032***	−0.240***	−0.257**
	(0.015)	(0.022)	(0.019)	(0.003)	(0.060)	(0.106)
Controls	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Observations	20223	19859	19285	20108	18820	17241
R^2	0.173	0.103	0.511	0.357	0.059	0.266
Panel B: SMEs with sole analyst (NOMAD or non-NOMAD)						
Dependent variables:	**R spread (1)**	**Amihud (2)**	**Roll (3)**	**Idio Rspread (4)**	**Idio Amihud (5)**	**Idio Roll (6)**
POST × NOMAD_research	−0.048***	−0.048***	−0.030*	−0.007**	−0.078**	0.018
	(0.011)	(0.016)	(0.018)	(0.003)	(0.036)	(0.077)
Controls	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Observations	10,513	10,498	9684	10,494	10,377	8523
R^2	0.181	0.078	0.466	0.340	0.054	0.267

In Panel B of Table 9, we concentrate on the subsample of SMEs covered by a single research analyst, and investigate whether there is any marginal benefit of that analyst being from the NOMAD. The coefficients on *POST × NOMAD_Research* are negative and significant across almost all columns, implying that sole research coverage provided by NOMADs has an incremental benefit. These results are in line with the findings in Section 4.1. Overall, the effect of unbundling reduces the profitability of equity research, which increases the risk that SMEs (in particular) lose coverage entirely. The institutional arrangements of AIM provide a brake on this process with positive effects on information provision and liquidity.

5 | CONCLUSIONS

In this paper, we examine the aggregate impact of unbundling on firm stock liquidity. Comparing market reactions to the announcement and implementation of MiFID II between the two sections of London Stock Exchange, we find that firms affected by unbundling on the Main Market experienced a substantial drop in both analyst coverage and stock liquidity and this drop is more pronounced for large-cap firms. However, on AIM both analyst coverage and stock liquidity increased post-MiFID II. Digging further into the AIM market, we find that the requirement to retain an corporate finance advisory firm (or NOMAD) who will often, but not always, also produce equity research can mitigate the shrinking research coverage driven by MiFID II unbundling. The close on-going relationship between the NOMAD and the company on the AIM enables a strengthened information channel, which can promote analyst-following and market liquidity. By decomposing liquidity into idiosyncratic and systematic components, we demonstrate that analyst coverage reduces firm idiosyncratic liquidity risk by enhancing the dissemination of firm-specific information.

Our findings are relevant to the ongoing debate in many countries about the merits of mandating unbundling rules. Recently, the UK's regulators has introduced new research unbundling exemption for SMEs, which is in line with our findings.[16] Our results suggest that unbundling may have unintended negative effects on the overall information environment and market liquidity. Although unbundling enhances competition among analysts, resulting in a better forecast quality, reduced analyst coverage worsens a firm's information environment and liquidity. However, these negative effects have been largely mitigated for firms listed on AIM by the regulatory requirement for NOMADs to be retained, in particular when the NOMADs also provide equity research, consistent with a strengthened information channel.

DATA AVAILABILITY STATEMENT

The data that support the findings will be available in Refinitiv Database following an embargo from the date of publication to allow for commercialization of research findings. Data subject to third-party restrictions. The data that support the findings of this study are available from Refinitiv.com. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at www.refinitiv.com with the permission of Refinitiv.

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REFERENCES

Acharya, V., & Pedersen, L. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, *77*(2), 375–410.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further us evidence. *Journal of Financial Economics*, *91*(1), 1–23.

Barth, M. E., & Hutton, A. P. (2004). Analyst earnings forecast revisions and the pricing of accruals. *Review of Accounting Studies*, *9*(1), 59–96.

Bradshaw, M., Ertimur, Y., & O'Brien, P. (2017). Financial analysts and their contribution to well-functioning capital markets. *Foundations and Trends® in Accounting*, *11*(3), 119–191.

Brennan, M. J., & Subrahmanyam, A. (1995). Investment analysis and price formation in securities markets. *Journal of Financial Economics*, *38*(3), 361–381.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, *22*(6), 2201–2238.

[16]See 'Changes to UK MIFID's conduct and organisational requirements': https://www.fca.org.uk/publication/policy/ps21-20.pdf.

Campbel, T. S., & Kracaw, W. A. (1980). Information production, market signalling, and the theory of financial intermediation. *The Journal of Finance*, *35*(4), 863–882.

Chan, K., & Hameed, A. (2006). Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics*, *80*(1), 115–147.

Charitou, A., Karamanou, I., & Lambertides, N. (2019). Analysts to the rescue? *Journal of Corporate Finance*, *56*, 108–128.

Claessens, S., Djankov, S., Fan, J. P. H., & Lang, L. H. P. (2002). Disentangling the incentive and entrenchment effects of large shareholdings. *The Journal of Finance*, *57*(6), 2741–2771.

Coller, M., & Yohn, T. L. (1997). Management forecasts and information asymmetry: An examination of bid-ask spreads. *Journal of Accounting Research*, *35*(2), 181–191.

Doukas, J. A., Kim, C., & Pantzalis, C. (2008). Do analysts influence corporate financing and investment? *Financial Management*, *37*(2), 303–339.

Easley, D., O'Hara, M., & Paperman, J. (1998). Financial analysts and information-based trade. *Journal of Financial Markets*, *1*(2), 175–201.

Fang, B., Hope, O.-K., Huang, Z., & Moldovan, R. (2020). The effects of MiFID ii on sell-side analysts, buy-side analysts, and firms. *Review of Accounting Studies*, *25*(3), 855–902.

Frenkel, S., Guttman, I., & Kremer, I. (2020). The effect of exogenous information on voluntary disclosure and market quality. *Journal of Financial Economics*, *138*(1), 176–192.

George, T. J., & Hwang, C.-Y. (2013, January 30). *Analyst coverage and two puzzles in the cross-section of returns*. AFA 2012 Chicago Meetings Paper. Available at SSRN: https://doi.org/10.2139/ssrn.1787152

Goyenko, R. Y., Holden, C. W., & Trzcinka, C. A. (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics*, *92*, 153–181.

Guo, Y., & Mota, L. (2021). Should information be sold separately? Evidence from MiFID II. *Journal of Financial Economics*, *142*, 97–126.

Hong, G., & Warga, A. (2000). An empirical study of bond market transactions. *Financial Analysts Journal*, *56*(2), 32–46.

Hong, H., & Kacperczyk, M. (2010). Competition and bias. *The Quarterly Journal of Economics*, *125*(4), 1683–1725.

Irvine, P. J. (2003). The incremental impact of analyst initiation of coverage. *Journal of Corporate Finance*, *9*(4), 431–451.

Jelic, R., Zhou, D., & Ahmad, W. (2021). Do stressed PE firms misbehave? *Journal of Corporate Finance*, *66*, 101798.

Jenkinson, T., Jones, H., & Rauch, C. (2022, August 14). *Long goodbyes: Why do private equity funds hold onto public equity?* Available at SSRN: https://doi.org/10.2139/ssrn.3753480

Kim, S.-H., & Lee, K.-H. (2014). Pricing of liquidity risks: Evidence from multiple liquidity measures. *Journal of Empirical Finance*, *25*, 112–133.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, *53*(6), 1315–1335.

Lang, M. H., Lins, K. V., & Miller, D. P. (2004). Concentrated control, analyst following, and valuation: Do analysts matter most when investors are protected least? *Journal of Accounting Research*, *42*(3), 589–623.

Lang, M. H., Pinto, J., & Sul, E. (2021). MiFID II unbundling and sell-side analyst research. *Journal of Accounting and Economics*, 101617. https://doi.org/10.1016/j.jacceco.2023.101617

Liu, M. H. (2011). Analysts' incentives to produce industry-level versus firm-specific information. *Journal of Financial and Quantitative Analysis*, *46*(3), 757–784.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), 483–510.

Mola, S., Rau, P. R., & Khorana, A. (2013). Is there life after the complete loss of analyst coverage? *The Accounting Review*, *88*(2), 667–705.

Moyer, R. C., Chatfield, R. E., & Sisneros, P. M. (1989). Security analyst monitoring activity: Agency costs and information demands. *The Journal of Financial and Quantitative Analysis*, *24*(4), 503–512.

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642–685.

Piotroski, J. D., & Roulstone, D. T. (2004). The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review*, *79*(4), 1119–1151.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance*, *39*(4), 1127–1139.

Roulstone, D. T. (2003). Analyst following and market liquidity. *Contemporary Accounting Research*, *20*(3), 552–578.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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