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Stock Liquidity and Company Annual Reports. How Does Publishing the Annual Report Affect Stock Liquidity?

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Abstract

Aim: This study examines how management reports affect stock liquidity and compares the responses of stocks with low, medium, and high liquidity.

Methodology: Stocks were classified into three liquidity groups based on the median Amihud (ILLIQ) ratio. The Wilcoxon test and the Mann-Whitney U test were used to verify the result. Lastly, quantile regression was used to show the role of initial liquidity levels, especially in higher quantiles.

Findings: The main findings show that management reports generally affect stock liquidity, but stocks with lower liquidity display a stronger reaction. This means that new disclosures, especially for companies that already have weaker liquidity, can create larger market fluctuations.

Implications: These results are significant for investors and market regulators because they can use the insights to better manage risk and make more informed decisions. From a managerial perspective, understanding how liquidity responds to disclosures can help companies refine their communication strategies. Researchers can also apply this event-based approach to study how other types of reports or market conditions influence liquidity.

Originality/value: Focusing on management reports and their impact on liquidity in a less-studied market and using both nonparametric tests and quantile regression make this research unique, helping to understand how stocks with low liquidity may show more changes after management disclosures.

Keywords: management reports, stock liquidity, event-based method, Wilcoxon test, quantile regression

1. Introduction

Stock liquidity has always been one of the central concepts in finance, influencing the cost of capital, portfolio risk, and how quickly the market reacts to new information (Będowska-Sójka, 2018). Although many studies have examined the impact of major financial announcements on liquidity, there has been less focus on the effects of annual management reports. These reports often include detailed operational information and managerial forecasts, which can cause notable changes in the behavior of traders and, as a result, in stock liquidity. From a practical viewpoint, understanding the influence of such reports is crucial for investors, policymakers, and companies as it supports better decision-making and risk management (Balakrishnan et al., 2014). Moreover, changes in investor risk aversion affect both stock returns and liquidity (Zhang et al., 2021), yet how annual management reports influence these liquidity dynamics remains largely unexplored.

The main goal of this study was to measure how management report publication influences stock liquidity. It also aimed to find out whether low liquidity stocks react more strongly to these announcements and how far the previous level of liquidity can predict these changes. To this end, the authors separated and compared stocks that typically exhibit low, medium, or high liquidity.

This article contributes to information asymmetry literature and the study of low-liquidity markets by addressing a research gap in how narrative annual reports influence trading behaviour. First, building on event study theory, it shows how management report publications – unlike short-term earnings announcements – can act as extended information events that reduce information asymmetry and trading frictions, thereby altering liquidity (Hope & Liu, 2023).This perspective expands the traditional event study framework by emphasising longer, narrative-based disclosures rather than short numerical announcements.

Second, while earlier studies focused primarily on large financial events, this study fills an empirical gap by examining annual management reports as distinct information shocks, especially relevant in emerging markets such as Poland, where evidence is limited (Naik & Reddy, 2021). Third, by differentiating liquidity groups, the paper identifies how market depth conditions moderate disclosure effects – an aspect rarely tested in prior studies.

The article begins by discussing the relevance of management reports to stock liquidity and their implications for investors, and then outlines the dataset and the classification of stocks by liquidity. In the empirical part, statistical methods are used to test the effects of management report disclosures across liquidity groups. This combined approach offers a novel contribution to the literature, particularly in the context of an emerging market. The findings show that while management reports influence stock liquidity overall, the effect is especially pronounced in low-liquidity stocks, which has important implications for investors and market stability.

2. Literature Review

Measuring liquidity precisely requires indicators that can capture its various aspects. This study focused on market liquidity, i.e. how easily a stock can be traded quickly without its price changing notably. Market liquidity has two primary components: transaction costs and price impact. Some indicators focus on transaction costs, such as the bid-ask spread. The simplest version is the quoted spread, which shows how much a trader must pay to place an immediate order (Beaupain & Joliet, 2011). A more advanced version is the effective spread, based on real transaction prices, even though methods like Roll's Measure can become less reliable if there is a strong price trend or extreme data points. The Corwin–Schultz method estimates the bid-ask spread using only daily high and low prices, which is helpful for event studies when intraday data is not available (Będowska-Sójka, 2018).

Theoretical frameworks, including signalling theory and information asymmetry, are relevant in this context. The signalling theory, first proposed by Spence (1973), argues that firms may employ disclosures to communicate reliable private information to the market, thereby shaping investor expectations and reducing uncertainty. In corporate communication, financial reports, including management commentaries, act as strategic indicators that connect insiders with external stakeholders (Connelly et al., 2011). Companies attempt to mitigate perceived risk and capture investor interest by offering more comprehensive or prospective information. The theory of information asymmetry claims that an unequal distribution of information results in mispricing, decreased liquidity, and wider bid-ask spreads. Disclosures are crucial for reducing these frictions. These theoretical frameworks are especially relevant for emerging markets like Poland, where formal analyst coverage is limited and investors depend largely on official reports. These concepts provide the foundation for assumptions about how management reports may influence market behaviour. By reducing information gaps and serving as credible signals, such reports can directly affect trading dynamics, especially where investor uncertainty is high. The following hypotheses were built upon this theoretical base.

Another group of indicators measures market depth to see how the price might change if a large volume of shares is bought or sold. These measures reveal how easily big trades can occur without shifting the price too much, but they do not include direct transaction costs. Tools such as the turnover ratio show the level of trading activity compared to the total number of shares, but do not capture the price impact of trades. A third category focuses on how trade volume affects prices. The Amihud Illiquidity Ratio (ILLIQ) is a well-known example that tracks the price response to trading volume, where higher values of ILLIQ mean the market is more sensitive, hence moderate trades can lead to bigger price moves (Będowska-Sójka, 2018). The Florackis Price Impact Ratio improves on this by including turnover, making it better for markets with different trading levels (Florackis et al., 2014). For event-based analysis, combining ILLIQ with the Corwin–Schultz method can be useful because the former reflects how price reacts to trade volume, while the latter estimates transaction costs without needing high-frequency data (Le & Gregoriou, 2020).

The event study methodology is theoretically grounded in the efficient market hypothesis (Fama, 1970), assuming that markets incorporate information into prices rapidly and unbiasedly. It is widely used in financial literature to assess the informational value of corporate disclosures, including earnings announcements and management reports (Holden et al., 2014). This framework allows researchers to examine how financial markets react to new public information, with a particular focus on changes in price and liquidity.

Prior empirical studies have explored how different types of corporate disclosures shape stock liquidity. Amiram et al. (2019) showed that enhanced information environments reduce jump volatility and improve liquidity, emphasising that the structure of volatility itself reflects informational efficiency. Balakrishnan et al. (2014), using a natural experiment, demonstrated that voluntary earnings disclosures causally narrow bid-ask spreads and increase trading activity, particularly among companies that lost analyst coverage. Zhang et al. (2021) revealed that investor sentiment and liquidity co-evolve, and that investor risk aversion plays a mediating role in how liquidity affects returns. These findings suggest that the effect of disclosures is context-dependent, and may be stronger where information asymmetry or trading frictions are high. Furthermore, Baruník and Čech (2021) argued for the use of quantile regression to capture heterogeneous effects across the liquidity distribution—particularly important when company-level liquidity varies widely. This motivated this article's empirical approach and supports the hypothesis that low-liquidity stocks exhibit stronger market responses to management reports.

Empirical studies show that corporate announcements may affect stock liquidity in different ways. Some suggest that financial disclosures reduce information asymmetry and narrow spreads, whilst others point out that disclosures can raise uncertainty. Pre-event conditions also matter in low liquidity stocks, higher transaction costs and information risks can bring about sharper changes. Stocks with higher liquidity tend to face fewer fluctuations due to more active trading and more efficient price discovery (Zhang et al., 2021). Many previous studies examined events such as earnings announcements and voluntary disclosures, whereas fewer studied how mandatory management reports impact liquidity. These reports can include forward-looking statements and operational details that impact investor expectations (Balakrishnan et al., 2014). Understanding how such disclosures affect liquidity can help with learning more about market efficiency, information asymmetry, and trading behaviour. By connecting this empirical literature with the theoretical models described earlier, one can form expectations about how different types of stocks respond to new information, especially when disclosure quality varies.

This paper examines the effect of these reports on stock liquidity, paying special attention to low, medium, and high-liquidity stocks. By using an event-based method the authors showed how market data changes when the reports are released, and addressed these gaps by applying both the Amihud ILLIQ and the Corwin–Schultz approach to study liquidity shifts following the publication of management reports. These two methods capture two main dimensions of liquidity – price impact and transaction costs – and suit short-term event-driven analysis. Building on prior research that links information asymmetry, signalling, and trading cost theories with market liquidity (e.g. Balakrishnan et al., 2014; Amiram et al., 2019; Zhang et al., 2021; Baruník & Čech, 2021), this paper extends the discussion to the context of management report publication. These frameworks suggest that disclosures reduce uncertainty and lower trading barriers, particularly in less liquid markets, providing the foundation for the following hypotheses.

H1: The publication of management reports affects liquidity.

This follows from the theory that financial disclosures reduce uncertainty and narrow information gaps, leading to measurable changes in liquidity indicators such as spreads, trading volume, and market depth.

H2: The strength of this effect depends on the pre-existing liquidity level, with stronger reactions expected for low-liquidity stocks.

Since less liquid stocks are more exposed to asymmetric information and transaction frictions, the influence of new disclosures is expected to be more pronounced in such cases.

H3: Low liquidity stocks experience greater volatility after the publication of management reports.

Due to limited trading activity and higher costs, these stocks are more vulnerable to abrupt price movements and liquidity shifts in reaction to new information.

To test these hypotheses, the authors relied on an event-based approach, the Wilcoxon test, and quantile regression, allowing to view liquidity behaviour across different parts of the distribution and among various types of stocks.

3. Methodology

This study applied an event study framework to examine changes in stock liquidity surrounding the publication of annual management reports. The analysis used daily data on prices and volumes from 60 companies listed on the Warsaw Stock Exchange. Liquidity was measured using two established indicators: the Amihud illiquidity ratio (ILLIQ), which captures the price impact of trading volume, and the Corwin–Schultz bid-ask spread, which estimates transaction costs.

For each company, pre-event and post-event liquidity were calculated as the average values of these indicators over a window of five trading days before, and three trading days after the publication date. The percentage change in ILLIQ and bid-ask spread represents the main dependent variables, showing how liquidity shifts after the report. To classify stocks by liquidity level, the median ILLIQ was computed for each stock across the entire sample period. Using the 30th and 70th percentiles, stocks were divided into low, medium, and high-liquidity groups.

The empirical analysis proceeded in three steps. First, the Wilcoxon signed-rank test examined whether liquidity significantly differed before and after the report within each group. Second, the Mann–Whitney U test compared liquidity changes between groups to identify which segments responded more strongly. Finally, quantile regression tested whether the pre-event liquidity level predicted post-event outcomes across different parts of the distribution, allowing for a deeper understanding of heterogeneous effects.

The event study approach is particularly appropriate for this research as it enables isolating the effects of management report publication from broader market dynamics by focusing on a defined event window. Prior research applied event study designs to assess how disclosures influence trading activity and liquidity (Krivin et al., 2003).

In this study, data were collected over a time window that included five days before each report and three days after it, hence market reactions both before and after a management report could be captured. Data for this study were obtained from PAP Biznes[1] for publication dates and from Stooq[2] for volume and price, ensuring comprehensive coverage of the 60 companies listed in the Polish stock market. For one of the companies (CBF), which did not have a management report for 2020, the authors used the previous year’s published data. This helps in detecting whether people might react to rumours or partial information emerging before the report, or if they wait a few days after the disclosure to act, without confusing such changes with regular market noise. As some key measures, particularly Amihud's ratio (ILLIQ), exhibited extremely high or outlier values, the data were weighted at the two percent level. Instead of removing these outliers completely, they were capped at the threshold of the 2nd and 98th percentiles, avoiding strong distortions in average values or other statistics that can occur when only a few very large outliers are present, while keeping the overall dataset intact. This pattern can be visually observed in Figures 1-3, which illustrate the distribution of raw, log-transformed, and spread-based liquidity measures change.

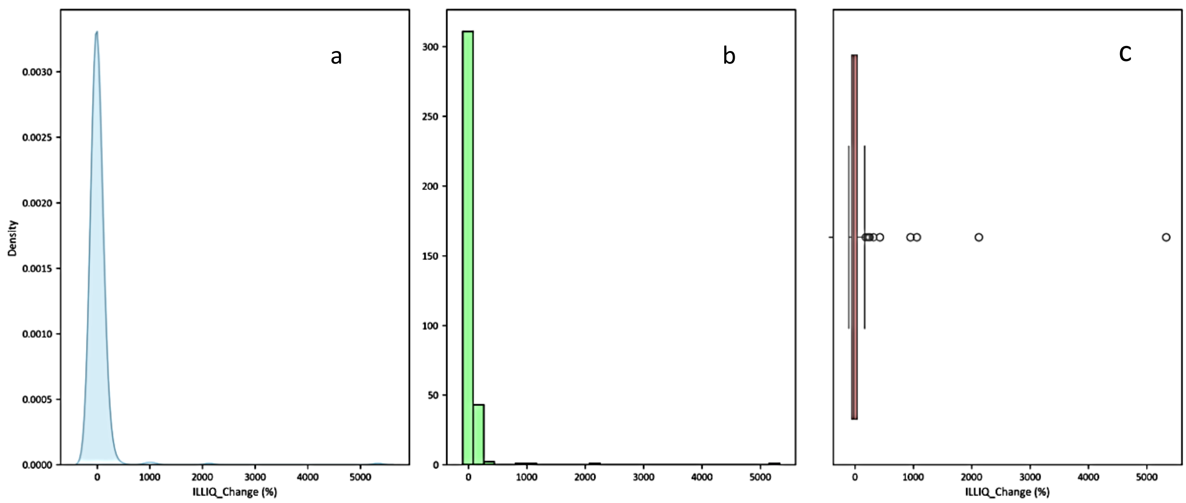

Fig. 1. Raw ILLIQ_Change (%) data a) KDE, b) Histogram, and c) Boxplot

Source: authors' own elaboration.

[1] https://biznes.pap.pl
[2] https://stooq.pl

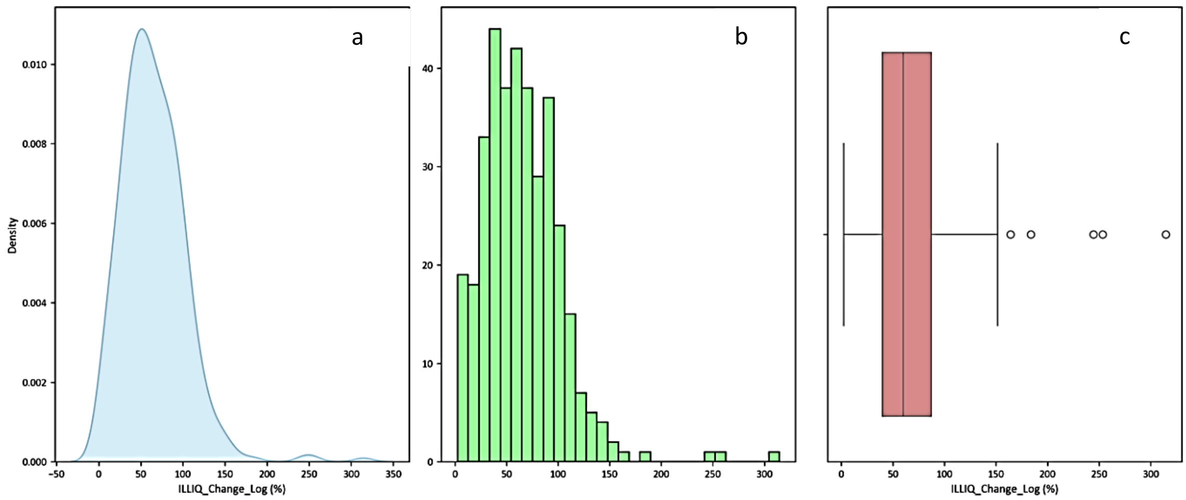

Fig. 2. Log ILLIQ_Change (%) data a) KDE, b) Histogram, and c) Boxplot

Source: authors' own elaboration.

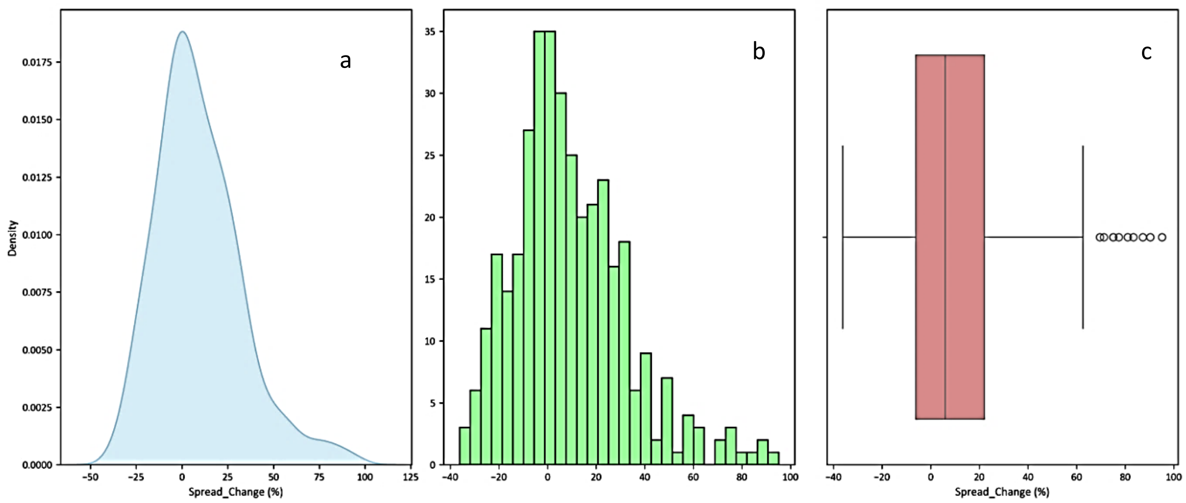

Fig. 3. Spread_Change (%) data a) KDE, b) Histogram, and c) Boxplot

Source: authors' own elaboration.

To split the stocks by liquidity level, the median Amihud ratio was calculated for each ticker symbol. Then, by looking at the 30th and 70th percentiles of these median values, three groups were defined. Stocks with median ILLIQ above the 70th percentile were considered low liquidity because their prices were strongly affected by trades. Stocks whose median ILLIQ was below the 30th percentile were considered high liquidity, as trade volume had less impact on their prices. The remaining 40 percent of stocks with mid-range median ILLIQ were placed in the medium liquidity group. Using 30-40-30 (instead of an equal split such as 33-33-33) handles skewed data more effectively and keeps the middle group large enough for stable results. By relying on each stock's median over the entire period, the typical liquidity level of each stock, rather than simply taking one day's data or an unstable average, was captured more accurately. Table 1 contains a list of companies that were classified using this methodology.

To compute the liquidity changes around the event, the pre-event and post-event measures were calculated based on daily averages. The pre-event ILLIQ was determined as the average Amihud ratio over the days prior to the event date, while the post-event ILLIQ was computed as the average over the days following the event. The ILLIQ change (%) was then calculated as the percentage difference between the post-event and pre-event ILLIQ. Similarly, the spread change (%) was obtained by calculating the percentage change in the bid-ask spread over the corresponding periods. In addition, a log-transformed version of the ILLIQ change, ILLIQ_change_log (%), was computed by taking the natural logarithm of the ratio of the winsorised post-event ILLIQ to the winsorised pre-event ILLIQ, multiplied by 100. These computations ensured that both the magnitude and the variability of liquidity changes were accurately captured and appropriately normalised.

Table 1. Liquidity Category

Liquidity Category	Low Liquidity	Medium Liquidity	High Liquidity
Ticker	ACG	1AT	BRS
	AMC	ACP	CDR
	ARH	AGO	CIG
	BFT	APR	CPS
	CAR	APT	DNP
	CMR	ATT	DVL
	DOM	BDX	ENA
	ERB	CCC	ENG
	FRO	ECH	EUR
	LPP	FTE	GEA
	NEU	GTC	JSW
	OPN	KRU	KGH
	PLW	KTY	OPL
	CBF	TXT	PGE
	SKA	LWB	PKN
	SNK	MAB	PXM
	STP	MDG	RFK
	WWL	MRC	TPE
		PCR	
		PKP	
		SLV	
		TOA	
		VRG	
		WPL	

Source: authors' own elaboration.

In this article, three statistical methods were used to examine how liquidity changes around the management report event. First, the Wilcoxon test was employed to check whether a significant difference in ILLIQ or spread existed before and after the report within each liquidity group. The test results were discussed later in the Results section. It was found that low and medium-liquidity stocks exhibited significant changes, whereas high-liquidity stocks did not show a significant difference in the raw Amihud data, even though the spread was still shifted noticeably. Next, the Mann-Whitney U test was used to compare liquidity changes among different groups. This test was applied to determine whether low-liquidity stocks differed significantly from high-liquidity stocks in terms of their ILLIQ changes around the report. Through this approach, it was clarified whether stocks with lower liquidity were more strongly affected by management reports.

Lastly, quantile regression was applied for a deeper look at how pre-report liquidity (as measured by the Amihud ratio) relates to post-report liquidity in different parts of its distribution. Quantile regression showed how stocks in higher or lower segments of the liquidity scale react, particularly useful if a stock that was already illiquid might face even harsher conditions after the report. This allowed to see if there was a bigger decline in liquidity in the higher quantiles (i.e. in worse liquidity scenarios). By combining an event-study framework with multiple complementary methods, both the direct effect of the report and the differences in how each liquidity group reacts, as well as the role of each stock's initial liquidity level were measured. Thus, the study not only investigated short-term changes tied to the management report but also was offered deeper insights into how more or less liquid stocks respond to new information.

To sum up, the following analysis applied these methods to examine the effect of management reports on stock liquidity. The upcoming results section presents detailed descriptive statistics, nonparametric test outcomes, and quantile regression estimates, which together show how liquidity responds to management reports in low, medium, and high liquidity stocks.

4. Results

Descriptive statistics show that low liquidity stocks experience much larger and more unpredictable changes in their Amihud ratio compared to medium and high liquidity stocks. For example, the maximum change in the low liquidity group can reach 5330.50, meaning that some stocks in this group become significantly less liquid after a report. Table 2 shows the detailed descriptive information for low liquidity group. In contrast, the maximum change in the high liquidity group is around 223.23, which is still large but much smaller than in the low liquidity group. The mean change in low liquidity stocks is around 44.95 percent, whereas in high liquidity stocks it amounts to 7.08 percent, suggesting that low liquidity stocks react more strongly to new information. Another important point is the median in the low liquidity group, approximately -26.91, indicating that half of the values fall below -27 percent; this demonstrates that some stocks improve their liquidity after a report, but the presence of very large positive values raises the overall average. The median in the high liquidity group is around -7.22 percent, indicating that many of these stocks' Amihud ratios have only slightly changed. Detailed descriptive information for the high liquidity group can be found in Table 3. The high standard deviation, particularly in the low liquidity group, confirms that changes vary greatly, with some stocks becoming less liquid while others are improving. For medium liquidity stocks, the mean change in the Amihud ratio is approximately 27.25 percent, with a standard deviation of 223.98 and a maximum change of 2122.87 (Table 4). Although these stocks still show the influence of extreme values, as evidenced by the skewness of 7.01 and kurtosis of 58.28, their behaviour lies between the extremes of the low and high liquidity groups. For the bid-ask spread, the results are relatively similar across the groups. The mean change in the low liquidity group is about 9.94 percent, in the medium liquidity group it is approximately 8.91 percent, and in the high liquidity group it is around 8.88 percent. This consistency suggests that while the Amihud ratio changes vary widely with liquidity, the spread changes remain more uniform.

Table 2. Descriptive Statistics for Low Liquidity

Statistic	ILLIQ_Change (%)	Spread_Change (%)	ILLIQ_Change_Log (%)
Count	108	108	108
Mean	44.9587	10.1796	59.2511
Std	520.3516	22.8581	37.1202
Min	-97.6115	-30.7992	3.2713
25%	-63.1449	-5.4352	33.0647
50%	-26.9164	5.9676	52.8000
75%	40.5935	22.6329	87.1439
Max	5330.5090	83.4070	183.7941
Skew	9.9795	1.0235	0.6609
Kurtosis	102.1500	1.2569	0.2664

Source: authors' own elaboration.

Table 3. Descriptive Statistics for High Liquidity

Statistic	ILLIQ_Change (%)	Spread_Change (%)	ILLIQ_Change_Log (%)
Count	108	108	108
Mean	7.083111	8.882704	68.58234
Std	62.806297	24.274973	27.962568
Min	-86.064579	-36.120933	13.046162
25%	-37.510131	-6.774856	50.111434
50%	-7.22433	3.172159	67.01487
75%	44.217177	24.181025	89.288732
Max	223.230238	95.15831	144.274614
Skew	0.909806	0.983353	0.215073
Kurtosis	0.590218	1.539544	-0.390044

Source: authors' own elaboration.

Table 4. Descriptive Statistics for Medium Liquidity

Statistic	ILLIQ_Change (%)	Spread_Change (%)	ILLIQ_Change_Log (%)
Count	144	144	144
Mean	27.247962	8.907769	67.154288
Std	223.981979	23.003245	44.564546
Min	-99.591515	-36.056202	2.415349
25%	-51.277688	-5.650008	39.686889
50%	-17.099882	7.807915	60.376671
75%	36.145111	19.925272	85.92761
Max	2122.870596	87.29392	314.538884
Skew	7.009735	0.7221	2.215897
Kurtosis	58.284669	0.884426	8.779846

Source: authors' own elaboration.

The log-transformed Amihud ratio change (ILLIQ_Change_Log) shows a mean of 59.25 percent in the low liquidity group, 67.15 percent in the medium liquidity group, and 68.58 percent in the high liquidity group. This log transformation reduces the impact of extreme values, while there is still considerable variability, particularly in the low liquidity group. The result of these calculation can be found in Table 6.

Combining all 360 observations, the mean ILLIQ_Change is 26.51 percent with a standard deviation of 319.49 and a maximum of 5330.50, resulting in a highly skewed distribution with a skewness of 13.77 and kurtosis of 217.89 (Table 5). The overall mean for the Spread_Change is 9.28 percent, while the overall mean for ILLIQ_Change_Log is 65.21 percent with a skewness of 1.60 and kurtosis of 6.93.

Table 5. Descriptive Statistics for all data

Statistic	ILLIQ_Change (%)	Spread_Change (%)	ILLIQ_Change_Log (%)
count	360	360	360
mean	26.5117	9.2098	65.2117
std	319.4948	23.2806	38.0845
min	-99.5915	-36.1209	2.4153
25%	-50.8759	-6.1184	39.9608
50%	-18.38738	5.9676	59.9769
75%	39.5512	22.1879	87.1965
max	5330.5090	95.1583	314.5388
skew	13.7753	0.8846	1.5996
kurtosis	217.8909	1.1598	6.9130

Source: authors' own elaboration.

Table 6. Liquidity and Spread Change Results pre and post event

Liquidity Category	Pre-Event ILLIQ	Post-Event ILLIQ	ILLIQ Change (%)	Spread Change (%)	ILLIQ_Change_Log (%)
High Liquidity	7.73E-08	5.48E-08	7.0831	8.8827	68.5823
Low Liquidity	4.16E-05	4.30E-05	44.9587	10.1796	59.2511
Medium Liquidity	1.73E-05	1.63E-06	27.247962	8.907769	67.154288

Source: authors' own elaboration.

In the Wilcoxon test, which compares before and after the report within each group, the authors computed the tests for raw data, winsorised data, and spread data. The results show that low and medium-liquidity stocks have statistically significant differences in the Amihud ratio – with p-values of 0.0037 (raw) and 0.0010 (winsorised) for low liquidity, and 0.0284 for both raw and winsorised data in medium liquidity – meaning that their liquidity changed notably after the report. In high-liquidity stocks, the change in the Amihud ratio is not significant (p-values of 0.2045 for raw and 0.2145 for winsorised data), although the bid-ask spread does change in a meaningful way ($p = 0.0091$); Table 7 shows the result related to this test. This suggests that high-liquidity stocks may maintain a more stable overall liquidity, but the spread can still shift in response to new information.

Table 7. Wilcoxon test results

Category	Type of Data	stat	p-value
Low Liquidity	Raw Data	1978	0.0037
	Winsorised Data	1855	0.0010
	Spread Data	1818	0.0004
Medium Liquidity	Raw Data	4121	0.0284
	Winsorised Data	4121	0.0284
	Spread Data	3445	0.0004
High Liquidity	Raw Data	2529	0.2045*
	Winsorised Data	2538	0.2145*
	Spread Data	2092	0.0091

Source: authors' own elaboration.

In the Mann-Whitney U test, which determines whether two groups differ in their liquidity changes, the authors examined both ILLIQ_Change (%) and ILLIQ_Change_Log (%). The test shows that there is a statistically significant difference between low- and high-liquidity stocks for both measures, with p-values of 0.0308 for ILLIQ_Change (%) and 0.0122 for ILLIQ_Change_Log (%), which matches the descriptive statistics indicating bigger shifts in low-liquidity stocks. No strong statistical differences were found between low and medium, or between medium and high liquidity (p-values above 0.16), implying that medium-liquidity stocks were not clearly distinguished from either group (Table 8).

Table 8. Mann-Whitney U test results

Metric	Category 1	Category 2	Statistic	p-value
ILLIQ_Change (%)	Low Liquidity	Medium Liquidity	7172	0.2919
ILLIQ_Change (%)	Low Liquidity	High Liquidity	4822	0.03085
ILLIQ_Change (%)	Medium Liquidity	High Liquidity	7039	0.1983
ILLIQ_Change_Log (%)	Low Liquidity	Medium Liquidity	7055	0.1893
ILLIQ_Change_Log (%)	Low Liquidity	High Liquidity	4681	0.01224
ILLIQ_Change_Log (%)	Medium Liquidity	High Liquidity	6985	0.1674
Spread_Change (%)	Low Liquidity	Medium Liquidity	7878	0.8593
Spread_Change (%)	Low Liquidity	High Liquidity	6081	0.5884
Spread_Change (%)	Medium Liquidity	High Liquidity	7900	0.8292

Source: authors' own elaboration.

Quantile regression examines how pre-report liquidity (the Amihud ratio) relates to post-report liquidity in different parts of the distribution, such as the 10th, 25th, 50th, 75th, and 90th percentiles. In the low liquidity group, the coefficient rose from around 0.0588 at the 10th percentile to about 1.0465 at the 90th percentile, demonstrating that if a stock already has low liquidity prior to a report, it may experience a much stronger drop afterwards when conditions worsen. This steep increase across quantiles suggests that the effect of pre-event illiquidity becomes more severe at the higher end of the distribution. In the medium liquidity group, the coefficients are smaller and increase more gradually, from 0.025 to 0.098, which indicates a positive effect but with much less variation across quantiles. In the high liquidity group, the coefficient ranges from around 0.225 to 0.4619, showing a moderate and more stable relationship compared to the low liquidity group. These differences indicate that the impact of pre-event illiquidity on post-report liquidity is highly dependent on both the level of initial liquidity and the position in the distribution. Furthermore, the extremely low p-values for the PRE_EVENT_ILLIQ coefficients across all quantiles underline the strong statistical significance of these relationships. Similarly, the intercept coefficients are statistically significant in most cases, reinforcing the robustness of the model. Sometimes the pseudo R-squared is negative, which can occur in certain quantile regression models if the linear form does not explain a particular percentile well. In the high liquidity group, the pseudo R-squared values increase at the 75th and 90th percentiles, indicating that the model provides a better explanation of liquidity changes in these higher percentiles (Table 9).

Table 9. Quantile Regression test results

Row (Category_Quantile)	Intercept_coef	Intercept_pval	PRE_EVENT_ILLIQ_coef	PRE_EVENT_ILLIQ_pval	pseudo_R2
High Liquidity_10th percentile	1.35E-08	1.38E-03	0.225217	7.67E-13	-0.070528
High Liquidity_25th percentile	2.11E-08	7.39E-07	0.251579	2.94E-18	0.090042
High Liquidity_50th percentile	3.22E-08	5.68E-09	0.293153	1.41E-16	0.217937
High Liquidity_75th percentile	4.64E-08	3.07E-07	0.36782	8.79E-13	0.311458
High Liquidity_90th percentile	6.29E-08	4.20E-05	0.461855	1.42E-07	0.381126
Low Liquidity_10th percentile	9.30E-07	1.25E-01	0.058812	1.31E-06	0.060026
Low Liquidity_25th percentile	1.56E-06	3.45E-02	0.093724	9.05E-11	0.08907
Low Liquidity_50th percentile	1.56E-06	4.95E-03	0.397241	1.42E-66	0.291712
Low Liquidity_75th percentile	4.33E-06	1.19E-05	0.448854	9.88E-60	0.42097
Low Liquidity_90th percentile	6.09E-06	2.21E-04	1.046542	2.03E-84	0.525781
Medium Liquidity_10th percentile	2.67E-07	2.59E-03	0.025468	1.66E-20	-0.071103
Medium Liquidity_25th percentile	4.34E-07	1.39E-06	0.027749	1.12E-23	-0.004776
Medium Liquidity_50th percentile	7.45E-07	4.21E-12	0.030479	2.23E-14	0.071189
Medium Liquidity_75th percentile	1.34E-06	9.16E-09	0.031925	1.38E-09	0.089193
Medium Liquidity_90th percentile	2.94E-06	4.44E-06	0.098716	4.62E-13	0.07744

Source: authors' own elaboration.

5. Discussion and Conclusion

This study firstly highlighted a research gap regarding the impact of management reports on stock liquidity in a market such as the Polish stock exchange. The effect was then assessed for stocks with different levels of liquidity (low, medium, and high) using an event-based approach and nonparametric statistical methods such as the Wilcoxon test, Mann-Whitney test U, and quantile regression. The data covered five days before and three days after each publication, and the authors applied a 2% winsorisation to handle outliers. Finally, based on the median Amihud ratio (ILLIQ), stocks were divided into three liquidity categories.

The key findings show that management reports generally affect stock liquidity. Stocks with lower pre-event liquidity displayed a stronger reaction after the report; for instance, low liquidity stocks showed a mean change of 44.71%, underlining the impact of management reports on these more fragile market segments. In most tests the difference between this group and high liquidity stocks was significant. These results indicate that management reports affect stock liquidity, low liquidity stocks experience sharper fluctuations due to information asymmetry and trading costs, while high liquidity stocks remain relatively stable despite changes in bid-ask spreads. The log transformation helps to lessen the impact of extreme values, but the inherent variability remains high when all stocks are considered together.

All these findings contribute to a better understanding of the initial hypothesis. The first hypothesis proposes that company reports influence stock liquidity. This is partially supported by the Wilcoxon test, which shows that, at least in low and medium liquidity groups, the Amihud ratio changes meaningfully following the report, whereas high liquidity stocks experience a significant shift in their spread. According to the second hypothesis, the impact is determined by the stock's liquidity. This is supported by differences between low and high liquidity stocks in the Mann-Whitney U test, as well as larger coefficients in low liquidity stocks in quantile regression. While the quantile regression results show consistent increases in coefficients across percentiles – particularly in the low liquidity group – formal statistical tests (e.g. the Koenker test) were not performed to evaluate whether these differences are statistically significant. However, the systematic variation across quantiles appears economically meaningful and suggests that the sensitivity of post-event liquidity to initial illiquidity increases toward the upper tail of the distribution. According to the third hypothesis, low liquidity stocks experience higher volatility following a report, whereas high liquidity stocks are less affected. The wide range of changes in the low liquidity group, as well as the significant differences shown by the Wilcoxon, Mann-Whitney, and quantile regression analyses, confirmed that low liquidity stocks respond more strongly.

From a theoretical viewpoint these results indicate that the concepts of information asymmetry and trading costs in low liquidity stocks can effectively explain their strong sensitivity to new disclosures. This insight encourages researchers to use combined methods, such as quantile regression in event-based analysis, and highlights the importance of separating stocks according to their pre-report liquidity level. For market participants and decision-makers, the study shows that low liquidity stocks, facing higher volatility risk, require more careful risk management or specialised strategies to take advantage of potential price swings.

The findings of this study are in line with the broader literature emphasising the role of financial disclosures in enhancing market liquidity. While the authors’ analysis focused on post-publication liquidity shifts, Amiram et al. (2019) provided evidence that more transparent disclosure environments reduce jump volatility, thereby improving liquidity – especially in settings with information asymmetry. Zhang et al. (2021) documented a causal link between investor risk aversion and subsequent changes in stock returns and liquidity. Although they do not explicitly compare the sensitivity of low versus high-liquidity stocks to new information, this study’s quantile regression results – showing stronger responses in higher illiquidity quantiles – offer a complementary perspective on heterogeneity in liquidity responses. Balakrishnan et al. (2014) pointed out that companies facing a loss of analyst coverage respond by increasing voluntary earnings guidance, which in turn significantly improves their liquidity – as reflected in lower Amihud ratios and narrower bid-ask spreads. While their focus is on voluntary forecasts rather than formal management reports, the mechanism of disclosure reducing information asymmetry and trading costs closely reflects with this study's findings.

However, there are certain limitations. First, focusing on data from the Polish stock market might restrict the generalisation of the findings to other markets, hence further research is needed to confirm or extend the results. Second, even though winsorisation reduces the impact of outliers, external factors e.g. macroeconomic changes or unexpected events may still influence stock liquidity over a short period. Future studies could examine different markets, longer time windows, and include additional informational factors, such as indicators of reporting quality or the intensity of voluntary disclosure, to achieve a more complete understanding of how stock liquidity evolves. Overall, the results show that management reports play an important role in influencing liquidity, especially in more vulnerable stocks, and open the door to further research in different markets.

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