



Do Generative AI Disclosure Narratives Affect Equity Valuation? The Mediating Role of Information Asymmetry in the Indonesian Capital Market around ChatGPT's Launch (2021–2025)

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Abstract. This study investigates the effects of the intensity of Generative AI (GenAI) adoption disclosure on company value and information asymmetry and whether asymmetry transmits the first effect to the second. This is of quantitative-explanatory-associative type. Nine inclusion criteria applied to non-financial LQ45 issuers on the Indonesia Stock Exchange left 46 firms and 172 firm-year observations from 2021 to 2025. Disclosure intensity comes from an original hybrid composite index. We constructed it by reading annual reports with massive language model support, attaching each positive score to a verbatim quotation, and a blind second coder returned Krippendorff's alpha of 0.805. Tobin's Q is a proxy for business value and the Corwin-Schultz bid-ask spread is a proxy for information asymmetry. I estimate the causal effect of using a chatbot to get help with homework using a combination of ordinary least squares regression with the Hayes PROCESS Model 4 mediation technique on 5,000 bootstrap resamples, a difference-in-differences test around the launch of the chatbot, and control-set sensitivity tests. All three tests concur. H3: GenAI disclosure does not impact firm valuation (1.130; $p = 0.101$). The coefficient on information asymmetry is 0.00100 and is insignificant ($p = 0.392$). The indirect effect through the spread is 0.005 and its 95 percent bootstrap confidence interval [-0.147; 0.161] comprises zero. Neither of the three possibilities is confirmed. The Indonesian issuers generally write operational and strategic narrative with little measurable responsibility and the market is not pricing it yet.

Keywords: Bid-Ask Spread; Firm Value; GenAI disclosure; Information Asymmetry; Tobin's Q

1 Introduction

ChatGPT became publicly available in November 2022, and within a single reporting period, generative artificial intelligence transitioned from a laboratory showcase to a topic on Indonesian company agendas. BCA, BRI, and Bank Mandiri have implemented extensive language model chatbots. Telkom, GoTo, and Bukalapak have inte-

grated GenAI into their customer service and product innovation. Certain aspects of that effort are included in the annual report. A significant portion of it does not, as Indonesian reporting regulations do not mandate companies to disclose any information regarding AI, nor do they provide guidelines on how to do so [1].

Adoption and pricing are separate questions. Our question is whether the Indonesia Stock Exchange (IDX) treats what issuers write about GenAI as information that belongs in the share price. Who is reading matters. Domestic retail accounts passed 14 million in 2024 [2], and a retail investor rarely gets a management meeting or an analyst call, so the annual report is close to the only document they have when forming a view of a firm's prospects. That view ends up expressed as firm value, the price a buyer would pay for the firm as a whole. Tobin's Q quantifies it, and the ratio does not solely account for historical cash flows; its numerator reflects the market's valuation of the intangible assets an issuer articulates. Indonesian data already indicates that tales are being valued. Voluntary disclosure is associated with capital expenditures, information asymmetries, and company valuation [3], non-financial disclosure affects the valuations of energy companies [4], and ESG disclosure adheres to a unique informational trajectory [5].

We do not expect that the revelation will have a direct impact on business worth. The route navigates information asymmetry, which is why asymmetry is integrated into our model as a mediator rather than a control or moderator. Contemplate the consequences when an organization diligently records its efforts with GenAI. The pool of private information held by management decreases, investors face less uncertainty, and a market maker is no longer necessary to sustain a wide bid-ask spread to safeguard against better informed traders. Diamond and Verrecchia delineated the sequence in a structured fashion [6]: disclosure narrows the spread, liquidity improves, the cost of capital falls, valuation rises. Each step depends on the step before it. That is a structure a mediation specification can estimate and a moderation specification cannot.

The data regarding the pricing of technology tales remains inconclusive. Companies revise their 10-K filings once they are aware that algorithms will be analyzing them [7]. Following the emergence of ChatGPT, companies with greater exposure to GenAI experienced an increase in value [8], banks that provided more information on AI shown enhanced profitability [9], and an AI-engagement index derived from filing text influenced stock prices [10]. Indonesian results push back. Voluntary non-financial disclosure has been found to depress firm value among energy issuers [4]. Sustainability disclosure came out insignificant for firm value in one domestic study [11], and uneven across its dimensions in another [12]. Neither body has absorbed the other, which is why the question is worth putting to Indonesian data.

Three deficiencies make Indonesia worthy of the endeavor. Investigations into AI disclosure have primarily concentrated on firms in the United States and China, neglecting the Indonesian context; local research suggests that AI adoption increases corporate value through an ESG-performance framework [13], but a GenAI disclosure index derived from annual reports in the Indonesian language has yet to be established. Global indexes serve as lexicons tailored to English-language 10-K disclosures, and the terminology utilized by an Indonesian issuer does not align seamlessly

with them [7], [10]. The mediation pathway is the third gap. No study we found tests it for AI disclosure in any emerging market, and the one recent domestic paper that puts information asymmetry in the model treats it as something arriving before disclosure rather than as the channel disclosure travels through [14].

We set out to test that pathway on Indonesian data, and the study carries three objectives. The first asks whether the intensity of Generative AI adoption disclosure in annual reports affects firm value, proxied by Tobin's Q, among LQ45 issuers on the IDX over 2021 to 2025. A second objective is whether the same disclosure affects information asymmetry, proxied by the bid-ask spread. The third question investigates whether information asymmetry acts as a mediator in the connection between the two. A single composite score would hide the variance in informational content that investors actually evaluate. We examine disclosure intensity using a combined content analysis of five sub-dimensions: strategic (S1), operational (S2), risk (S3), governance and oversight (S4), and demonstrable impact (S5). The investigation is contextualized by the theories of agency and signaling. Reliability of the coding index was checked by an external second coder. This yields two results: early evidence as to whether a growing market rewards the clarity of frontier technology integration, and a story of how Indonesian blue-chips represent such integration.

2 Literature Review

2.1 Equity Valuation, Agency, and Signaling

Firm value here means the market's assessment of a whole firm against the assets it already holds. Tobin's Q states that assessment as one ratio, the market value of equity plus the net book value of liabilities divided by total assets [15]. Each half of the ratio does different work. Above the line sits the market's forward-looking judgment of the cash a firm can generate, including capability the balance sheet never records, while below the line sits the historical cost accounting recognizes. Intangible capability falls between the two, and a technology narrative is a claim about that space. A firm priced above one trades for more than its recorded asset base. Below one it does not. Our question is therefore narrow: whether GenAI disclosure shifts the numerator while the denominator stays where accounting left it.

Agency theory treats the principal-agent relationship as a standing conflict of interest that rests on information asymmetry and surfaces in the market as an adverse-selection discount, priced as monitoring, bonding, and residual-loss costs [16]. Read through that lens, GenAI disclosure is a bonding device. Management moves part of its private information into the public record when the annual report describes GenAI strategy, implementation, and risk, and aggregate agency costs compress. None of this changes fundamental cash flows. What changes is the market's information about them, which is why we place information asymmetry as the causal link between what a firm discloses and what its equity is worth.

Signaling theory is stricter than a first reading suggests. A signal carries information only in a separating equilibrium, where it costs a high-quality type less than an

imitator, so imitation does not pay [17]. Price the signal alike for everyone and it collapses into cheap talk. GenAI disclosure clears that bar only when its costs fall unevenly: a technology roadmap exposed to competitors, litigation and reputational damage over AI-washing claims, scrutiny over undelivered promises. Firms without real capability have little reason to pay that bill. Buyers who cannot separate good from bad push prices down, and market makers widen the spread to protect themselves, so spread width measures asymmetry [18]. Diamond and Verrecchia give the route from disclosure to liquidity to valuation its formal statement [6], threshold models explain why a manager publishes only what pays to publish [19], [20], and an empirical survey collects the evidence [21].

2.2 Prior Studies on AI Disclosure, Information Asymmetry, and Equity Valuation

Previous research exists in three categories that this study integrates. The initial connection links AI transparency to worth and efficacy. Financial institutions that provide greater transparency regarding AI demonstrate enhanced profitability [9], companies amend their filings upon realizing that algorithms will analyze them [7], and organizations with increased exposure to Generative AI experienced favorable anomalous returns following the emergence of ChatGPT [8]. An engagement metric for artificial intelligence, created using natural language processing, tracks prices [10], whereas an alternative study highlights the influence exclusively in scenarios when the government serves as an intermediary [22]. A collection of legal risks linked to AI disclosure outlines the financial ramifications. The second component shifts from revelation to informational inequality. The adoption of XBRL reduces information asymmetry among Indonesian issuers [24], whereas disclosure, capital expenses, asymmetry, and value engage in a reciprocal relationship within a significant domestic sample [3]. The third element pertains to the documentation of domestic mediation. On 67 manufacturing issuers, the earliest study found intellectual-capital disclosure lowering asymmetry, which then carried through to firm value [25]. Later work takes up different constructs, with mixed results. Asymmetry came out insignificant on a sustainability construct [26], an ESG mediation path was insignificant too [5], and non-financial disclosure has at times been priced negatively [4], though digitalization evidence [27] and Vietnamese signaling evidence [28] point the other way. So the asymmetry mediation path has not been consistently confirmed here, and no GenAI disclosure index exists for Indonesian issuers.

2.3 Hypothesis Development

Signaling makes a clean prediction about valuation. Substantive GenAI disclosure works as a costly separating signal, since only firms with genuine capability can carry the proprietary, litigation, and reputational costs of writing in detail, so an investor reads intensity and specificity as evidence of quality that is otherwise hidden and pays a premium for it [17]. Outcomes from developed markets corroborate the forecast [7], [8], [22]. The pace of implementation is increasing among IDX issuers [1], and the

beneficial impact of AI adoption on value has been validated in Indonesia [13]. Both patterns indicate that the domestic market may have entered a stage where GenAI disclosure is a valuable signal. The degree of generative AI adoption disclosure in annual reports positively influences firm value, as indicated by Tobin's Q, for LQ45 issuers on the IDX.

Detailed voluntary disclosure compresses the uncertainty an investor carries, narrows the spread of valuations across investors, and shrinks the adverse-selection component of the bid-ask spread [6]. A market maker who already knows what a firm is doing with GenAI has less risk to price into the quote. The empirical record supports this. Firms moving to transparent reporting regimes see spreads narrow [29], XBRL adoption lowers asymmetry domestically [24], and disclosure is reciprocally tied to cost of capital and asymmetry on the IDX [3]. The degree of generative AI adoption disclosure adversely influences information asymmetry, as indicated by the bid-ask spread, among LQ45 issuers on the IDX.

The mediation hypothesis follows almost by construction from the disclosure-liquidity framework. Disclosure first lowers perceived information asymmetry, a narrower bid-ask spread follows and liquidity improves, the cost of capital falls, and firm value rises [6]. Each link waits on the one before it. That constitutes a chain, not a contingency; hence, the specification must be a mediation model instead of an interaction. Indonesian precedent is present: for 67 manufacturing issuers, utilizing the bid-ask spread as the asymmetry indicator and Tobin's Q as the valuation metric, mediation was established, allowing the chain to operate within the framework of this market [25]. H3: The bid-ask spread, representing information asymmetry, influences the relationship between the intensity of generative AI adoption disclosure and the value of firms listed in LQ45 on the IDX.

3 Methodology

The design is quantitative and explanatory-associative, connecting GenAI adoption disclosure, information asymmetry and economic value. The analytical unit we have is the firm-year. The graphic displays a cross-sectional view of LQ45 ingredients on IDX with a temporal chronology from 2021 to 2025. H1 and H2 are claims of direct impacts, thus we use ordinary least squares (OLS) regression with control variables to evaluate them. H3 is a mediation hypothesis and we use the bootstrap methodology of the Hayes PROCESS Model 4 [30]. The five-year period is intentional: it captures the launch of ChatGPT in November 2022, allowing for a difference-in-differences study.

Sampling is purposeful and begins with the LQ45 elements. The deepest liquidity on the exchange (bid-ask spread which is needed in daily form). The highest motivation to publicize technology efforts. Quite homogenous data. Then nine inclusion criteria restrict the selection. A firm must have been in LQ45 for at least four of the ten semi-annual rebalancing windows (K1) and completed a comprehensive annual report: MD&A, a five-page strategy review, full governance part (K2). Under IDX-IC, it must be in a non-financial industry, equal to JASICA code 8x (K3). A financial balance sheet renders the market-to-asset ratio unequal. Additionally, we need at least

240 valid trade days for the Corwin-Schultz estimator to converge (K4) [31], and positive book equity in at least four of five years (K5). Homemaking on four screens Functional currency is Rupiah or consistent exchange conversion (K6). Fiscal year ending 31 December, which aligns the November 2022 shock across firms (K7). No material restatement (K8). No material corporate action (K9). This leaves us with 46 unique issuers and 172 firm-year observations, sufficient for an OLS regression with about 20 parameters and a Hayes PROCESS Model 4 bootstrap, which typically requires 100 to 200 observations. A separate topic, addressed in the restrictions, is what size effect a sample this tiny can detect. We independently re-collected every variable from primary sources. Three firm-years were combined numbers, one small GenAI-index modification, and no inferential conclusion modified.

Firm value is the dependent variable. We compute it as Tobin's Q, following Eq. (1).

$$Q = [MVS + (AVCL - AVCA) + AVLTD] / TA \quad (1)$$

In Eq. (1), MVS is the market value of equity, AVCL and AVCA the average book values of current liabilities and current assets, AVLTD the average book value of long-term debt, and TA total assets [15]. GenAI disclosure intensity is the independent variable. We operationalize it through an original hybrid composite index covering five subdimensions and twenty binary items: strategic (S1), operational (S2), risk (S3), governance and oversight (S4), and measurable impact (S5). Each item takes a score of 0 or 1. Each subdimension also carries a quality score of 0 to 3, and Eq. (2) combines the two.

$$Composite = 0.60 \times Binary + 0.40 \times Quality \quad (2)$$

We divide the total binary score by 20 for the binary index and the total quality score by 15 for the quality index.

Coding is done using a standardized dictionary of operational definitions, keyword lists, decision rules, and boilerplate exclusions using a large-language-model-assisted content-analysis process. We start by passing each firm-year through a highly accurate AI/GenAI phrase filter. If a valid term is not found, a source-based zero is assigned to the firm-year. When a signal arrives, we read the report page by page, rejecting decoy phrases as we read. All binary scores of 1 must be associated with a verbatim quote and page number and we have verified all positive ratings word-for-word against the source. Reliability was tested at the item level for 20 firm-years (or 20 items) on a subsample of 400 binary judgments. That subsample was recoded by a second coder who was blind to the first. Krippendorff's alpha and Cohen's kappa both round to 0.805 (0.8050 and 0.8048 respectively), with 97.2 percent agreement, over the customary 0.70 standard. One caveat here. High raw agreement partially reflects agreement on non-disclosure, with 57.6 percent of observations at zero. The subdimension dependability is sufficient for strategic (alpha 0.804) and operational (alpha 0.825), weaker for governance (alpha 0.385), whereas risk and measurable impact show negligible variance in the sub-sample.

Information asymmetry is the mediator. We estimate it annually as the bid-ask spread, using the unadjusted Corwin-Schultz method on daily high and low prices over two consecutive trading days, averaged across the year. The method needs no intraday quote data [31]. Four substantive controls enter the main model. Size is the natural logarithm of total assets. Leverage is total debt over total assets, and Firm Age is the observation year minus the IPO year [32]. The fourth control is a Big-4 auditor indicator [33]. Three conventional variables stay out on purpose: ROA and Growth risk acting as bad controls, and Board Independence varies too little among LQ45 firms. All three are back in the sensitivity testing. Estimation was done in IBM SPSS Statistics 26 using the Hayes PROCESS v4.3 macro and again in a separate Python pipeline, each coefficient cross-reconciled. Continuous variables are winsorized at the 1st and 99th percentiles and inference is based on standard errors clustered at the company level. Where classical-assumption tests revealed violations we changed the specification, not the data, keeping all 172 observations: a log transformation of the dependent variable, feasible generalized least squares with variance weighting, and Prais-Winsten for first order autocorrelation. We check for robustness using a difference-in-differences test around November 2022, a value-per-employee outcome substitution, a five-step control-set sensitivity analysis and left-censoring diagnostics using a Tobit model and a two-part decomposition.

4 Results and Discussion

4.1 Descriptive Statistics

The final sample holds 172 firm-year observations from 46 LQ45 issuers between 2021 and 2025. Table 1 sets out the descriptive statistics. Continuous variables in the main model are winsorized at the 1st and 99th percentiles; ROA, Growth, Board Independence and Value per Employee, kept for the robustness work, stay on their original scale.

Mean Tobin's Q is 1.164, so the typical LQ45 issuer trades a little above the book value of its assets. The median sits lower, at 0.757, so the distribution leans right. GenAI_Index behaves differently again. Its mean is 0.099 and its median is zero, because 57.6 percent of firm-years carry no GenAI adoption disclosure we could anchor to a verbatim quotation. A programming mistake would not have generated zeros of that order. Such disclosures were uncommon in 2021, by less than a quarter of issuers, and unevenly distributed thereafter. The weight is unequal throughout the index. The mean item scores are 1.023 for the operational subdimension and 0.453 for the strategic one, as opposed to 0.192 for governance, 0.076 for risk and 0.035 for measurable impact. The index tops out at 0.740 across the whole panel, so the variation available to the regressions is narrow. Size averages 31.663 in natural logarithms, Leverage averages 0.431, and 95.9 percent of the sample is audited by a Big-4 affiliate, the ordinary large-cap profile.

Table 1. Descriptive Statistics

Variable	N	Mean	Std. Dev.	Minimum	Median	Maximum
Tobin's Q	172	1.164	1.314	0.041	0.757	7.371
GenAI_Index	172	0.099	0.147	0.000	0.000	0.740
Bid-Ask Spread	172	0.0082	0.0022	0.0043	0.0079	0.0140
Size (ln total assets)	172	31.663	0.944	29.362	31.579	33.748
Leverage	172	0.431	0.191	0.041	0.443	0.803
Firm Age (years)	172	23.221	11.300	1	25.5	48
Big4 (dummy)	172	0.959	0.198	0	1	1
ROA	172	0.079	0.082	-0.126	0.067	0.454
Growth	171	0.124	0.292	-0.528	0.067	2.197
Board Independence	170	0.438	0.117	0.286	0.400	0.833
Value per Employee (ln)	171	22.426	1.325	19.567	22.379	26.146

Source: authors' computation from IDX market data and audited annual reports (2026).

4.2 Classical Assumption Tests and Correlations

The determination of the models' specification was done using four classical-assumption tests. The problem of multicollinearity was never an issue, as diagnosed by tolerance and variance-inflation. Three other assumptions were wrong. Residuals were not normally distributed (Shapiro-Wilk $W = 0.865$; $p < 0.001$), variance was not constant (Breusch-Pagan $p = 0.001$) and Durbin-Watson was 0.878. We fixed all three in the spec, not the data, thus all 172 observations stayed in. Logging Tobin's Q raised W to 0.984 and passed Kolmogorov-Smirnov at $p = 0.225$. The weighted residuals passed Breusch-Pagan for feasible generalized least squares ($p = 0.768$). The Durbin-Watson was 1.984 again ($\rho = 0.929$) after the Prais-Winsten AR(1) transformation. The correlation matrix tells a similar story, more simply. The GenAI_Index is not significantly correlated with Tobin's Q ($r = 0.032$, $p = 0.67$) and with the bid-ask spread ($r = 0.021$, $p = 0.79$). The largest correlation of Tobin's Q is size, $r = -0.392$ ($p < 0.001$).

4.3 Hypothesis Testing

All All three hypotheses were examined using firm-clustered OLS regressions with controls and sector dummies included. The mediation test for H3 used 5,000 bootstrap resamples of the percentile. All coefficients were cross-checked between SPSS and Py-thon. The results are shown in Table 2.

H1: Heavier transparency adds to firm value The coefficient of GenAI_Index on Tobin's Q is positive, 1.130 but does not clear the 5 percent mark (clustered standard error 0.688; $p = 0.101$; R-squared = 0.381). On the log scale, the coefficient drops to 1.218 with $p = 0.060$, still below 5 percent. Reject H1. Size is negative and significant ($p = .006$) therefore the specification holds and the missing GenAI effect is not an artifact of a weak model.

H2: Disclosure intensity is expected to reduce knowledge asymmetry. The path-a coefficient of GenAI_Index on the bid-ask spread is 0.00100, negligible at $p = 0.392$ and the sign is contrary rather than consistent with the prediction. H2 is not supported.

H3 predicted that the disclosure impact will pass over to the value via the expected information asymmetry. The indirect effect $a \times b$ is 0.005 with a 95% bootstrap confidence interval of $[-0.147; 0.161]$ that includes zero. Path b is 5.48 with $p = 0.922$, the direct effect c' is 1.124 with $p = 0.114$, and the Sobel z is 0.097. H3 is not supported. If the chain is unbroken it has no starting link..

Table 2. Summary of Hypothesis Testing

Hypothesis	Path	Linear Q: coef (p)	ln Q: coef (p)	Conclusion
H1	GenAI $\rightarrow$ Firm value	1.130 (0.101)	1.218 (0.060)	Not supported
H2	GenAI $\rightarrow$ Information asymmetry	0.00100 (0.392)	0.00100 (0.392)	Not supported
H3	Mediation via bid-ask spread	0.005 $[-0.147; 0.161]$	0.046 $[-0.063; 0.183]$	Not supported

Source: authors' computation, SPSS 26 and Python cross-reconciled estimates (2026). H3 reports a bootstrap interval, not a p -value.

4.4 Robustness Checks

The other specifications all kept the null. In a difference-in-differences test surrounding the debut of ChatGPT, we obtained an insignificant interaction coefficient ($p = 0.470$). When the dependent variable was replaced by Value per Employee, the coefficient on the GenAI_Index was negligible at 1.038 ($p = 0.177$; $N = 171$). In the five-step control-set sensitivity analysis the coefficient was consistent and non-significant, p between 0.101 and 0.724, N between 169 and 172. It didn't alter with fixed firm and year impacts. So did raw unwinsorized data, and a subsample estimated without the Big-4 control. One aspect of the data warrants special consideration. Since 57.6 percent of data are zero, GenAI_Index is left-censored and we fitted a Tobit model and a two-part decomposition. Both have systematic zeros. On the intense margin, we find no evidence of any latent H1 signal ($p = 0.921$), and only a time trend significantly predicts whether a firm discloses at all ($p = 6.0e-6$). The whole index is traced by a compact index generated from S1, S2 and S4 at Spearman 0.9994 and returns the same null, therefore the building of the index is not the explanation.

4.5 The 2021 to 2025 Trajectory around the ChatGPT Launch

The regressions compress five years into a handful of coefficients. Table 3 traces the annual path of disclosure and valuation across the window, computed from the same 172 firm-year panel.

Table 3. Annual Means of GenAI Disclosure, Equity Valuation, and Information Asymmetry around the ChatGPT Launch

Year	N	GenAI_Index	Firms disclosing (%)	Tobin's Q	Bid-Ask Spread
2021	35	0.047	22.9	1.250	0.0086
2022	35	0.057	31.4	1.346	0.0079
2023	37	0.073	37.8	1.233	0.0078
2024	35	0.156	65.7	0.996	0.0080
2025	30	0.173	56.7	0.965	0.0088

Source: authors' computation from the 172 firm-year panel of IDX market data and audited annual reports (2026).

The news spread swiftly. The average GenAI_Index increased from 0.047 in 2021 to 0.173 in 2025, nearly quadrupling, while the share of issuers with any verifiable GenAI disclosure increased from 22.9 percent to 65.7 percent in 2024, declining to 56.7 percent in 2025 even while average intensity continued to grow. The valuation was the other way. Average Tobin's Q was 1.250 in 2021, 1.346 in 2022 and 0.965 in 2025. The mean bid-ask spread scarcely moved, sitting at roughly 0.008 during the timeframe. The non-significant difference-in-differences interaction is reported as a single coefficient ($p = 0.470$) that the two series diverge, which is re-stated from the other side as the Tobit result that a temporal trend alone predicts the decision to reveal ($p = 6.0e-6$). And we interpret this table as a description and stop. These are unconditional annual averages without controls; the decline in Tobin's Q is muddled by market-wide movements unrelated to GenAI; and the 2025 row is based on only 30 observations as coverage thins out. The LQ45 membership is rotational and the panel is imbalanced by design. The above tested models have causal weights. What the trend does tell us is that the null was not born of a quiet period: Disclosure propagated swiftly among LQ45 issuers in the very window we analyzed, although valuation did not change with it.

4.6 Discussion

Even a null this steady still tells something, read through the logic behind it. A signal is only effective if it is costly and hard to copy [17]. There was little to no third party AI audit and quantifiable AI revenue in LQ45 issuers, with GenAI disclosure mostly consisting of cheap narrative around operations and strategy. Revealing that shape is cheap talk, not a separating signal, and a null finding for Tobin's Q (H1) is what cheap talk predicts. Both the information-asymmetry and the voluntary-disclosure arguments arrive at the same conclusion, that is, disclosure reduces the information gap only when it is credible and informative [18], [6], [19]. What Indonesian issuers write is dominated by unverifiable qualitative assertions, thus there is little price-relevant content to absorb, which is why the effect on the bid-ask spread minimal (H2) and why mediation (H3) has no path-a to build on. Two structural elements point to the same thing: filtering is real and the decision to disclose is driven by a time trend, and conventional fundamentals dominate a developing market where firm size is the only

substantial driver of Tobin's Q. What we contribute is early evidence that GenAI disclosure is not yet price-relevant in Indonesia, a description of an adoption anatomy weighted toward operational and strategic narrative over measurable risk and impact accountability and an index whose item level reliability is high (Krippendorff's $\alpha = 0.805$) even where sub-dimension reliability is uneven. Any regressions produced, that instrument remains.

5 Conclusion

Equity valuation in this context relates to Tobin's Q, which evaluates the market value of equity in relation to net liabilities and total assets; thus, the inquiry posed in our title is if a GenAI story affects the market's evaluation of a company regarding its current assets. The reply is unfavorable. We examined 172 firm-year instances from 46 LQ45 issuers spanning 2021 to 2025, and none of the three predictions were validated. The advent of GenAI does not significantly influence the company's worth (H1). It does not succeed in diminishing information asymmetry (H2), and in the absence of that crucial link, the bid-ask spread remains minimal, rendering the mediation in H3 ineffective. We subsequently attempted to invalidate the null hypothesis but were unsuccessful. The difference-in-differences analysis conducted at the time of the launch, along with a dependent-variable substitution, five-step control specifications, censored models, and fixed effects, all yielded the same negligible coefficient; a streamlined version of the index produced the same result, so eliminating the possibility of an artifact arising from index building. The depicted illustration is entirely consistent. The disclosure spread swiftly after the advent of ChatGPT, despite the unconditional average Tobin's Q experiencing a downturn exacerbated by prevailing market conditions, although the distribution remained constant. The report offers an analysis of that revelation, which is still in its early stages and inconsistent, mostly concentrating on operational and strategic narratives but deficient in measurable risk and impact responsibility. At present, none of it serves as a dependable, verified indicator, and an Indonesian market in this embryonic phase of distribution does not attribute worth to what it cannot validate.

Certain constraints characterize that reading. The construction of the index required considerable effort and relied on the discretion of the coders; however, each affirmative score is substantiated by a direct quotation, and all 306 instances were confirmed, yielding a Krippendorff's α of 0.805. A five-year period is brief, and 57.6 percent of the firm-years attain a score of zero, resulting in less variability than desired. Our issuers are substantial, listed on the LQ45, and rather homogeneous, which constrains regressor variability and biases estimates toward the null: the minimal effect identifiable at 80 percent power is approximately 1.93, compared to an observed effect of 1.13, or 59 percent of the benchmark. We indicate the lack of a discernible effect, rather than proof of no effect. Two adverse Tobin's Q values, authentic metrics for cash-abundant issuers, were addressed through winsorization. The approach warrants a re-evaluation over an extended timeframe and in areas where the usage of AI has advanced. Regulators can interpret the disparity among subdimen-

sions as a rationale for AI-disclosure directives that encourage issuers to provide verifiable information, including third-party validation and quantifiable effects, so enabling disclosure to function as a signal. At this juncture, GenAI disclosure holds greater value for issuers and investors as a means of strategic communication rather than as a tool for valuation. Subsequent research may expand the scope by using large-language-model coding and integrating moderating variables into the framework. We would additionally prefer the user perspective to be evaluated explicitly, utilizing surveys or controlled tests to understand how investors interpret and assess GenAI storylines, as market-level statistics can merely suggest that perception phase.

Authors' Contribution and Acknowledgment

Author roles ran as follows. The corresponding author conceived the design, built the GenAI disclosure index, ran the analysis and drafted the manuscript, while the second author supervised the research and critically revised the paper. Our third and fourth authors validated the results and their interpretation. We disclose our use of a large language model as a tool, applied to the content analysis of annual reports and to manuscript editing. All data, coding and statistical analysis were verified independently by the authors. Every positive score is anchored to a verbatim quotation checked word-for-word against its source page. Full responsibility for the content rests with the authors.

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