Would I lie to you?

On Private Equity Intermediary Reports

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March, 2025

Private equity fund managers provide interim valuations for portfolio companies, which exhibit systematic biases due to valuation smoothing. These reports also contain extensive qualitative disclosures, offering valuable insights beyond the reported Net Asset Values (NAVs). While existing research has examined the informational value of interim NAVs in private equity (PE), the accompanying qualitative disclosures remain underexplored. We put together a new international dataset of more than 25,000 General Partner (GP) deal reports. Our dataset allows us to analyze two new areas. First, the data includes detailed quantitative metrics for portfolio companies, such as sales, EBITDA margins, and valuation multiples. To our knowledge, this is the first study to integrate these interim quantitative data and decompose NAV figures to provide richer insights into portfolio dynamics. Second, we leverage over 600,000 sentences of qualitative commentary from these reports to analyze the qualitative information that GPs use to describe portfolio performance. Results show that narrative tone is a robust predictor of final investment outcomes. Deals with more optimistic interim tone achieve significantly higher final multiples on invested capital (MOIC), even after controlling for quantitative performance metrics. Tone is particularly informative at the time of fundraising and, unlike interim valuations, positive tone consistently predicts final multiples across GP locations and deal regions. Machine learning algorithms show that the informational value of GP reports is high since these methods achieve accurate predictions of final deal performance. Our findings suggest that GPs strategically use qualitative disclosures to complement information and communicate expectations to Limited Partners (LPs). This behaviour aligns with a double agency dynamic, where both GPs and LPs navigate competing incentives to balance transparency with reputational considerations.

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We thank participants at the Private Equity Research Consortium in Oxford (2024), the Private Markets Research Conference (2023), the Columbia Private Equity Research Conference, and seminar participants at London Business School and SKEMA Business School for their comments and suggestions. We acknowledge and appreciate the data access, cooperation and enriching discussions with members of Unigestion, S.A. We are also grateful to SKEMA Business School for providing financial support for the project.
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1. Introduction

In private equity, Limited Partners (LPs) supply capital to General Partners (GPs), who then deploy this money into various investments. This process may create agency conflicts, as GPs spend significant effort in selecting, managing, and exiting investments while holding private information about their quality (Axelson et al., 2007; Robinson and Sensoy, 2013). A key tool for addressing these concerns is periodic performance reporting. As in mutual fund and hedge fund reports, private equity reports typically feature a summary statistic - the Net Asset Value (NAV) - alongside qualitative information.[6]

While existing research has examined the informational value of interim NAVs in private equity (PE), the accompanying qualitative disclosures remain underexplored, with notable exceptions such as Biesinger et al. (2020).[7] This paper bridges this gap by introducing a novel dataset of more than 25,000 GP reports from Europe and North America, ensuring broad applicability across the two largest private equity markets.[8]

Our dataset allows us to analyze two new areas. First, the data includes detailed quantitative metrics for portfolio companies, such as sales, EBITDA margins, and valuation multiples. To our knowledge, this is the first study to integrate these interim quantitative data and decompose NAV figures to provide richer insights into portfolio dynamics. Second, we leverage over 600,000 sentences of qualitative commentary from these reports - approximately 35 sentences per interim NAV figure - to analyze the qualitative information that GPs use to describe portfolio performance.

We use tone analysis to determine if GPs' descriptions of portfolio companies are positive or negative. Our main tone measure is generated by FinBERT. FinBERT provides a score for each report from -1 (highly negative) to +1 (highly positive) using a neural network model designed for financial documents (Huang, Wang, and Yang, 2023).[9] On average, tone is moderately positive at 0.24 across deal reports, but with substantial variation across reports (standard deviation is 0.35). Regional

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[6] As in previous papers, we use the term NAV to denote the Fair Value of investments reported by GPs to LPs. Unlike Net Asset Value (NAV), which reflects the overall value of a portfolio including liabilities such as management fees and carried interest accruals, Fair Value focuses purely on the market value of the investments, excluding such liabilities. This approach provides an unbiased assessment of the valuation and reporting practices applied by private equity firms.

[7] They examine the relationship between the description of the value creation plan of the GP and the subsequent performance of the investment.

[8] In this paper, private equity investments are broadly defined as leveraged equity investments in profitable private companies. This means that we select both controlling investments in profitable companies, which are usually Leveraged Buy-Out, and labelled as such, and non-controlling investments in profitable companies (growth equity).

[9] Huang, Wang, and Yang (2023) train their model using three types of financial texts: corporate filings, financial analyst reports, and earnings conference call transcripts. They show that their FinBERT model outperforms other methods to gauge tone in the financial context, including the dictionary of Loughran and McDonald (2011). FinBERT is publicly available on GitHub (https://github.com/yya518/FinBERT).

differences are notable, with North American deals displaying a more optimistic average tone (0.34) than European investments (0.20). Report tone is closely associated with valuation mark-ups and mark-downs in the following report: 45 percent of mark-ups are preceded by a positive tone in the previous report, while 38 percent of mark-down are preceded by a negative tone report.

Our central finding is the consistently significant relationship between the tone in intermediary reports and investment performance, proxied by the Exit Multiple on Invested Capital (MOIC), or the MOIC uplift, constructed as the difference between the Exit MOIC and the interim MOIC in the report.[10] For example, a simple sorting of reports into positive and negative tone, reveals striking differences in final outcomes: the average deal with a positive interim tone report has a 0.52 points higher MOIC uplift than the average deal with a negative tone (i.e., 0.83 vs 0.31). Tone is also highly influential in a multivariate regression setting where we control for interim valuations as well as fund and deal characteristics. Our estimates show that a one-standard-deviation increase in report tone translates into a 0.24x higher MOIC uplift evaluated at mean. Meanwhile, a one-standard-deviation increase in interim MOIC translated into an 0.07x higher MOIC uplift evaluated at mean. Report Tone remains highly statistically significant throughout the life of the investment, especially in the early years of the investment when there is significant uncertainty and room for growth. Meanwhile, interim MOIC only predicts MOIC uplift in the first two years of the deal's life.

Results are robust to multiple robustness tests including variations of the FinBERT tone measure and the construction of alternative tone measures using other Large Language Models (i.e., FinRoBERTa), earlier machine learning models, and the use of other methods such as the dictionary-based methodology used in Loughran and McDonald's (2011). Additional robustness tests show remarkable consistent influence of interim report tone across subsamples splitting among types of investment, GP experience, fund size, exit deal performance and investment duration.

Our finding suggests that GPs have information or insights into future portfolio performance – these insights are not reflected in reported NAVs. Since GPs have discretion in deciding how to distribute this information between current NAVs and qualitative disclosures, the significant impact of tone suggests they choose to convey some of this information through the qualitative narratives in their reports.

Additional results also reveal that in situations where NAVs may be more biased, GPs compensate by embedding corrective signals in textual narratives. This dynamic is particularly relevant during fundraising periods, when GPs seek to raise new capital. At such times, LPs face the critical challenge

[10] Performance is measured as the ratio of total cash proceeds divided by total cash invested (MOIC; Multiple of Invested Capital). MOIC is gross of all fees and fund expenses.

of deciding whether to reinvest and therefore have a heightened need for accurate performance information. Prior research indicates that GPs tend to present favorable results while fundraising.

We test whether the predictive power of tone is amplified during fundraising, by examining deal reports from such periods. We hypothesize that textual narratives take on greater importance at such times. Consistent with this hypothesis, we find that the correlation between interim tone and MOIC uplift is approximately 25% stronger during fundraising periods compared to non-fundraising periods. This suggests that GPs may use tone as a signaling tool to attract investors. Notably, while interim quantitative metrics, such as MOIC, show weaker correlations with final performance during fundraising, tone maintains its predictive strength. The effect is particularly pronounced for established PE firms, who seem to be leveraging reputational capital to rely more heavily on qualitative signals rather than on quantitative metrics solely.

Our sample also allows to explore differences in the use of report tone and interim valuations across regions. Although our sample includes deals from all over the world, we constrained the deals to be in North America and Europe only to achieve better homogeneity. Splitting the deals across deal location in either Europe or North America leads to strikingly different results. Positive interim tone consistently predicts higher MOIC uplift or Exit MOIC across countries, but the relationship between interim valuation measures and final returns is the opposite for European and North American deals. The results are the same if we split the sample across GP location. The different influence of interim valuation measures contrast with the results in a recent concurrent paper (Ercan et al., (2024), which focuses on interim valuations and does not analyze tone. Our findings suggest that GPs around the world use positive tone in interim reports to signal good news, but do not do the same in terms of interim valuations. It is possible that the maturity of the market and the sophistication of LPs in both sides of the Atlantic are an important reason of the differences found.

Overall, our findings highlight the important role of qualitative information in GPs' communication strategies. GPs appear to strategically choose how to convey their knowledge about portfolio future prospects - whether through fair value estimates or qualitative narratives. A natural question that arises is whether the complete informational set in GP reports, encompassing both qualitative and quantitative elements, is predictive of ultimate performance. If such a prediction turns out to be possible, it would suggest that GPs provide valuable insights through multiple complementary channels rather than withholding information.

We apply machine learning (ML) algorithms to show that investors could have indeed predicted outcomes with the information contained in GP reports. Trained on interim data, our models exhibit remarkable predictive accuracy for final deal outcomes. For instance, both Lasso regression and Random Forest models achieve strong predictive performance (ROC-AUC between 0.76 and 0.77) in identifying outperforming deals, measured by the ability to outperform the median Exit MOIC of the deals exited in the same year, as early as one year after entry. Deals predicted to outperform deliver a mean exit MOIC of 3.34x, which is almost double the Exit MOIC of deals predicted to underperform (1.70x). Extending this analysis using information from the entire investment horizon and predicting the MOIC uplift, reveals an even greater economic impact: deals in the highest quartile of predicted performance achieve a mean MOIC uplift of 1.63x, compared to just 0.15x for the lowest quartile. The ML findings reinforce the idea that these reports contain relevant forward-looking information.

Altogether, our findings suggest that GPs have an understanding of the eventual investment outcomes. Given this knowledge, at each reporting interval, GPs face the strategic decision of how to allocate their expected value uplift between the reported NAV and the accompanying qualitative narrative. While NAVs, for example, may reflect a more conservative estimate subject to smoothing, GPs could use report tone to complement or substitute communication of optimistic or nuanced expectations. This dual approach allows GPs to manage how they convey performance to investors, strategically balancing between quantitative figures (NAV) and qualitative insights, depending on the investment's current performance and context.

A central question arising from this interpretation of the results is why GPs opt to disclose valuable insights in textual narratives rather than embedding them directly in NAVs, or withholding them altogether. The double agency model described by Morris and Phalippou (2012) offers a possible explanation for this behavior in the PE industry. This model identifies a "principal," such as trustees or regulators, overseeing multiple asset classes but lacking specialized expertise. These principals rely on agents with PE knowledge - such as internal pension fund divisions or external consultants (e.g., Hamilton Lane or StepStone) - to allocate capital to GPs through multi-year contracts. The relationship creates layered incentives and reporting challenges.

GPs issue quarterly NAV reports, complemented by more detailed mid-year and year-end written updates. Prior research has shown that NAVs are often "smoothed," inflating values for underperforming investments and understating those of outperformers, thereby enhancing Sharpe ratios. These ratios are then reported by LPs to their principals. While LPs recognize this inflation, they often tolerate it as higher Sharpe ratios can lead to increased budgets, staffing, and fees.

However, LPs periodically assess whether to reinvest with GPs. Such decisions may require a more accurate picture of the underlying performance of investments. This creates a scenario where GPs have an incentive to complement biased NAVs with more precise qualitative disclosures. Given the large number of LPs - often numbering in the hundreds - GPs cannot rely solely on verbal communications to convey nuanced insights. Written reports thus serve as a scalable and systematic channel for disseminating soft information alongside NAVs.

Our results may have important policy implications. NAVs reported by PE funds are crucial for investors like endowments and pension funds. Misstated NAVs can distort returns, leading to poor decisions, like incorrect university spending or miscalculations in pension fund contributions and distributions. It also misaligns performance-based compensation, causing excessive bonuses at times, and insufficient bonuses at other times. Investors could create more accurate estimates using interim reports but may lack the right incentives. Increasingly, regulators require independent and more accurate NAV estimates, especially as open-ended structures grow. In these structures, transactions need to occur at NAV and if there a litigation risk whenever the NAV is biased. Our results show the GPs could produce better quantitative information (NAVs) if they wanted to, and/or independent auditors could produce better NAVs based on what GPs would communicate to them.

Our paper contributes to the growing body of research on the reliability and biases of PE valuations. Brown et al. (2019) show that while underperforming managers may inflate NAVs during fundraising periods, this manipulation is identified by investors. Jenkinson et al. (2020) examine the alignment of NAVs with realized cash flows, finding minimal bias in buyout funds on average but a positive bias in venture capital funds, particularly in the post-2000 era. Huther (2022) finds that NAV markdowns are most pronounced within the first 18 months of an investment, and are larger for later-stage investments of low-reputation funds. Ercan et al. (2024) demonstrate that interim markdown frequencies and valuation staleness are predictive of future returns, with higher interim marks often linked to weaker future performance.

Our study contributes to this literature in several distinctive ways. While most prior research has focused on fund-level NAVs, more recent studies have shifted towards deal-level valuations. We advance this trend by not only examining deal-level NAVs, but also decomposing them and analyzing the full breadth of additional information provided in GP reports. This information includes a time-series dataset of quantitative portfolio company financials as well as qualitative commentary, from which we derive tone measures. Moreover, we provide evidence that findings from U.S. markets may not fully translate to other geographies, such as Europe, which has become nearly as significant as the U.S. in terms of market size.

Our work also intersects with broader debates on the balance between public and private information in financial markets. Previous research has shown that sell-side analysts may issue overly optimistic stock recommendations to attract retail investors while reserving valuable private insights for institutional clients (e.g., Hirshleifer et al., 2024; Malmendier and Shanthikumar, 2007; Gu et al., 2019; Li, Mukherjee, and Sen, 2021). Similarly, GPs in PE face competing incentives in their disclosure strategies, balancing the need for transparent reporting with the selective sharing of private information. However, unlike public markets - where overly positive tone in earnings press releases is often linked to weaker future performance (Huang et al., 2014)- our findings suggest that positive tone in private equity GP reports is associated with stronger final investment outcomes. This indicates a distinct and strategic use of qualitative information in private markets.

Finally, our research ties into the broader literature on the linguistic analysis of financial texts, which has leveraged psychology- and finance- specific dictionaries to quantify tone. Early work in this area includes Tetlock (2007), Tetlock, Saar-Tsechansky, /and Macskassy (2008), and Hanley and Hoberg (2010), who applied psychology dictionaries to financial texts. Loughran and MacDonald (2011) developed financial-market-specific dictionaries, which have since been used to analyze tone in contexts such as Dow Jones newswires (Da, Engelberg, and Gao, 2011), *New York Times* financial articles (Garcia, 2013), 10-K filings and IPO prospectuses (Jegadeesh and Wu, 2013), corporate press releases (Ahern and Sosyura, 2014), earnings calls (Fu et al., 2021), and wire news from Factiva (Huang, Tan, and Wermers, 2020).[11]

2. Data

2.1. Data collection

Our dataset originates from a Fund-of-Funds with investment strategies spanning a broad array of private market funds but concentrating on Buyout funds and exhibiting a modest European tilt. All investee funds are required to submit regular reports that offer both portfolio valuations and qualitative assessments of investment progress. [12] While some fund managers (GPs) provide quarterly

[11] See for an overview also the survey article by Loughran and McDonald (2016).

[12] A standard report typically encompasses: a Summary Letter, a Performance Overview, a Schedule of Investments, a Portfolio Company Update, a Capital Account statement, and Financial Statements

reports, the majority adhere to a semi-annual reporting schedule (end of June and end of December). Consequently, our analysis is confined to the reports produced for these semi-annual periods. It should be noted that only the year-end report is audited.

For each report, we calculate the MOIC by dividing the total value by the total capital invested up to that point. Total value is the sum of the NAV and cumulated proceeds up to that point. We calculate MOIC uplift as the difference between Exit MOIC and the interim MOIC in the report. We select private equity funds with vintage years between 2000 and 2015. The latest batch of reports are from June 2024. Table 1 shows the filters we apply to arrive to our final sample.

The initial sample includes 25,103 reports coming from 1,932 unique buyout investments, i.e., an average 12.4 reports per investment. The mean (median) total investment value is €195.8 million (€57.9 million), and the mean (median) Exit MOIC is 2.26x (1.91x).

To gain in homogeneity, we further reduce our sample by focusing on funds operating in Europe and North America, leaving 23,265 observations. The average total investment value is similar and the average (median) exit MOIC remains practically unchanged at 2.26 (1.88). Note that quantitative information in reports is provided in different currencies across our sample. For performance-related variables, such as MOIC, we retain the original deal-denomination to reflect the native context of each investment. However, when assessing size, whether at the deal or fund level, we standardize these figures in Euros to provide a comparable basis across observations.

Since we rely on textual descriptions of current performance and future prospects at the deal and semester levels, we apply an additional filter requiring at least one sentence of such data in reports. This reduces our sample to 20,454 reports from 1,795 firms. This means that 98% of firms (and 88% of reports) have available textual data. Importantly, neither the total value in a given semester nor the Exit MOIC change substantially. Averages are actually being slightly lower than in the overall sample of European or North American buyout or other PE deals. Textual data is missing for 12% of reports, with no significant structural patterns that we could detect. It is slightly less common during periods of fundraising and more frequent for older deals. If anything, missing text is slightly more frequent for high-performing deals.

Finally, another unique feature of our data is that we observe financials time-series data for a large number of reports. This allows us to empirically analyse the informational value of deal tone and interim MOIC beyond current firm performance. We have 17,219 semesters from 1,727 unique firms with complete information on firm sales, EBITDA, net debt, and enterprise value. The mean (median) total value increases slightly to €201.8 million (€60.0 million), while the exit MOIC remains stable at 2.29x (1.91x). Firms are tracked for an average of 12.6 semesters, and tone data continues to be available for 84% of the observations.[13] The patterns in Table 1 give us confidence that the filtering process does not result in any systematic biases in the data we use for our analysis.

2.2. Measuring tone in GP reports

The most recent development in assessing the tone in financial disclosure is to use Large Language Models (LLMs) specifically fine-tuned for financial documents. The most common model is FinBERT, developed by Huang, Wang, and Yang (2020). This model is based on the BERT (Bidirectional Encoder Representations from Transformers) architecture originally proposed by Devlin, Chang, Lee, and Toutanova (2019). The FinBERT model is fine-tuned on a vast body of financial documents, including corporate annual and quarterly filings, financial analyst reports, and earnings conference call transcripts. Its effectiveness stems from its ability to capture both semantic and syntactic nuances in the text, significantly outperforming traditional tone analysis methods like the Loughran and McDonald's (2011) dictionary and earlier machine learning models.[14]

In our analysis, we calculate tone scores using FinBERT by following a structured process. First, we extract the text of the company section in each GP report and tokenize it into sentences using the NLTK sentence tokenizer. Each sentence is classified as negative (-1), neutral (0), or positive (1) by FinBERT, and we compute the average tone score for all sentences related to a given investment in a given report.

For robustness, we compute two alternative measures. The first is FinRoBERTa, which builds on the RoBERTa (Robustly Optimized BERT) architecture. RoBERTa improves upon BERT through optimized training, such as dynamic masking and training on a broader corpus that includes BookCorpus, English Wikipedia, CC-News, OpenWebText, and Stories datasets. FinRoBERTa is further pre-trained on financial data, making it suitable at interpreting financial language. Like FinBERT, FinRoBERTa classifies sentences into negative, neutral, or positive categories, with scores

[13] We have 107 investments that are publicly traded at least one semester throughout the holding period. We tested the robustness of all results in this paper by excluding these semesters and deals, but given their small number, it is unsurprising that the findings remain unchanged.

[14] For example, consider the sentence: "Although the global market is experiencing a downturn, food companies are doing well thanks to Covid." Traditional NLP techniques, such as word2vec, often fail to assess such statements accurately because they analyze words independently without understanding contextual relationships. FinBERT, in contrast, uses its transformer-based architecture to interpret the tone in the context of the sentence, identifying positive implications for food companies despite the broader negative market tone.

aggregated to yield an overall tone score. Table 4 shows that the correlation between FinBERT and RoBERTa is high at 0.83.

The second alternative approach employs the Loughran and McDonald (2011) dictionary-based model, which relies on a predefined set of words associated with positive or negative tone in financial contexts. This method calculates tone as the ratio of (positive words – negative words) / (positive words + negative words + neutral words), where neutral words are those not included in the Loughran and McDonald (LM) word list[15]. Although this method is simpler and widely used, it lacks the contextual sensitivity of FinBERT and FinRoBERTa. Its correlation with FinBERT is at 0.61 (and at 0.57 with RoBERTa). By employing these complementary measures in robustness tests, we ensure that our tone analysis captures the nuanced tone of financial disclosures and that our findings do not rely on the choice of tone metric.

2.3. Final sample descriptives

Table 2 provides the descriptive statistics of our final sample at the semester (Panel A) and the investment level (Panel B), respectively. Panel A shows that the unweighted mean (median) interim MOIC is 1.52x (1.09x), indicating a distribution skewed by a few high-performing deals. The MOIC uplift, which represents the delta between the Exit MOIC and the interim MOIC at the time of each report, has a mean (median) of 0.66 (0.28), suggesting moderate value creation on average. However, the high standard deviation of 1.64 highlights substantial variability in uplift across deals. Notably, the realization share, which measures the degree to which a shareholding is sold, has a mean (median) of 0.17 (0.00), reflecting that most investments are unrealized at the time of the reports.

The average (median) number of sentences in the report is almost 10 (8). We use these sentences to create our qualitative measure of report tone. Report Tone, as measured by FinBERT, has a mean (median) value of 0.23 (0.25), suggesting a slightly positive overall tone in textual disclosures. The standard deviation of 0.36 indicates significant heterogeneity in tone across deals, underscoring the subjective nature of qualitative assessments.

Our paper is one of few only that also provides granular financial metrics. Sales, reported in millions of Euros, have a mean (median) of 733.5 (170.0), illustrating a broad spectrum of firm sizes in the dataset. Profitability, as measured by the EBITDA margin, averages 0.18 (0.15), while the

[15] Note that, because the tone measure computed using the LM word list relies on individual words rather than sentences, as in LLMs, the number of tone observations may differ between the two methods.

EBITDA valuation multiple has a mean (median) of 9.0x (8.3x). Financial leverage, proxied by Debt/EV, has a mean (median) of 0.59 (0.61).

Regarding fund metrics, 15% of reports occur during the fundraising periods of the next fund with the same fund strategy. The average (median) report occurs when the funds is 5.7 (5.0) years old, corresponding to the mid-lifecycle of a typical PE fund. The average (median) fund generation is 4.1 (4.0). Importantly, over 90% of reports are audited by one of the Big Four firms, ensuring high data reliability and credibility.

Panel B of Table 2 presents a bivariate analysis of exit MOIC and average FinBERT tone across various dimensions at the investment level. The majority of deals in our final sample are buyout investments. The exit MOIC is nearly identical between buyout and other PE deals, with buyouts showing an average (mean) exit MOIC of 2.22x and other PE investments higher at 2.56x. The tone is slightly more optimistic for other PE deals, with an average tone of 0.27 compared to 0.23 for buyouts.

Approximately two-thirds of the sample consists of European investments, which exhibit a lower average exit MOIC of 2.24xx than the average MOIC of 2.34x for North American deals. This represents a slight underperformance of European investments of about 4.3% on average. Similarly, the average FinBERT tone for European investments is considerably lower at 0.20, whereas North American investments show a more optimistic tone, with an average of 0.32. This is more than a 38% difference in terms of tone.

A large portion of the sample consists of fully realized deals (1, 380 investments, 77%). Adding partially realized deals results in an 87% share (1,566 out of 1,795) of realized deals. Fully realized investments show the highest average exit MOIC at 2.57x, compared to 2.13x for partially realized deals and just 0.60x for unrealized ones. As observed in previous studies (e.g., Braun et al., 2020), unrealized investments tend to exhibit lower exit MOICs, likely reflecting their incomplete lifecycle. However, this does not necessarily imply lower potential quality, as we will observe when analyzing the time-series of key variables in the subsequent table. Supporting this interpretation, the average tone for unrealized deals (0.14) is lower than for realized ones (0.25).

Finally, the sample is evenly distributed across different investment duration categories. Deals with a holding period of 3 to 4 years deliver the highest returns, with an average exit MOIC of 2.73x and an average tone of 0.28. Conversely, investments held for six or more years show significantly lower performance, with an average exit MOIC of 1.97 and an average tone of 0.22. This finding is consistent with prior research (e.g., Joenväärä et al., 2021), which suggests that longer holding periods often correspond to investments encountering operational or market-related challenges.

Our sample offers a representative snapshot of deals within the global PE landscape, particularly focusing on European leveraged buyouts (LBOs) while also including a significant subset (20%) of North American LBOs. This dual focus enables us to test for regional differences in Buyout. Comparatively, our sample's performance metrics compare well with those reported in Ercan et al. (2024), who analyse U.S.-based LBO and venture capital (VC) deals. Their mean and median size-weighted final Multiple of Invested Capital (MOIC) among buyouts and other PE deals are 2.35x and 1.95x, respectively. For our U.S. subset of 453 investments, we find slightly lower corresponding numbers: 2.34x (mean) and 2.08x (median). These differences also include a larger greater standard deviation in their sample (2.2 versus our 1.46). Overall, the size-weighted mean and median MOIC for our full sample, spanning both European and North American deals, stand at 2.16x and 1.83x, respectively.

Table 3 presents time-series statistics for interim MOIC, Report Tone (FinBERT), and the realization share over a deal's lifetime for fully realized deals. Since we use semi-annual reports, Year 1 refers to the second report available after the investment is initiated. For instance, if a deal closes in July 2012, Year 1 would correspond to the report from June 2013. To enhance transparency regarding the evolution of these key variables, we categorize the sample of 1,380 deals by deal duration. Panel A focuses on interim MOIC, revealing that investments with durations up to six years exhibit a consistent increase in value over time, culminating with a significant jump at exit (i.e., in the deals' final year). Deals remaining in the portfolio for extended periods, above six years in our sample, do not exhibit such a MOIC uplift at exit and generally represent less successful investments. Notably, the fact that the MOIC at entry is not zero can be partially explained by the semi-annual frequency of our sample. Additionally, investments fully liquidated within the first four years after closing exhibit the highest MOIC at entry, suggesting that GPs may prefer a shorter holding period immediately following the transaction.

Panel B explores average FinBERT deal tone of reports leading up to exit. Report tone shows no obvious time trend over a deal's life. Deals remaining in the portfolio for extended periods, above six years in our sample, have average tone between 0.21 and 0.24, which are lower than the report tone of other categories. In our multivariate analysis of the following sections, we will carry out robustness checks on abnormal FinBERT tone, and other report tone measures to ensure our findings remain consistent.

Panel C examines realization shares. This panel shows that the dominant distribution pattern in our sample corresponds to the sale of no more than 20% of shares in the years leading up to exit. The average realization shares in the final years are 100% as one might expect. (The exception is the category of deals with the longest holding periods, for which we have averaged the realization shares of all years beyond the sixth year.) The majority of total proceeds are realized during final sales upon full exit, highlighting a key characteristic of PE deal structures. This finding is particularly relevant to our analysis, as it emphasizes that GP text reports primarily focus on future prospects rather than retrospective or current performance. Nonetheless, we will take into account the realization share in our multivariate analyses of the next sections.

3. Intermediary tone and final deal returns

3.1. Main analysis

Before carrying out a multivariate analysis of the relationship between interim Report tone and MOIC uplift and Exit MOIC, we first examine some descriptive patterns of Report tone in relation to other variables of interest. In Table 4, variables are grouped into the same three investment-level categories as in Panel A of Table 2: value-related variables, qualitative information, and quantitative financial metrics.

The data shows that all three measures of Report tone exhibit a highly significant positive correlation with interim MOIC and an equally strong positive correlation with future MOIC uplift. This already suggests that tone captures valuable information about the future trajectory of a deal's value. Among all correlations (outside those with alternative measures of tone), the strongest correlation for FinBERT Report tone is the negative association with markdown frequency. On the other hand, Report tone is significantly positively correlated with company financial metrics: higher sales, profitability, or EBITDA valuation multiples are associated with more optimistic tone. Conversely, tone is negatively correlated with leverage levels, likely reflecting the heightened financial risk associated with increased debt. Importantly, these descriptive patterns hold consistent across the two alternative tone measures, reinforcing the robustness of these findings.

Commented [LP1]: Why start with this? Its a detail and not interesting right?

In Table 5, we show the average MOIC uplift (Exit MOIC – Interim MOIC) and MOIC variation (Mark-up, Stale, Mark-down) compared to the next report (t+1) across categories of current (t) tone (Positive, Neutral, Negative). The results show a relationship between the current tone of reports and subsequent MOIC changes. Positive tone reports are associated with the highest proportion of mark-ups (44.5%) and the largest mean MOIC uplift (0.83x, significant at 1% level). Neutral reports show a more balanced distribution of valuation changes and moderate uplift (0.56x). Negative reports show the lowest mean uplift (0.31x), but we observe a less clear pattern in the short term. A negative tone is almost as likely to result in no change in valuation (37.0%) as in a mark-down (37.9%).

To test the correlation between Report tone and future investment prospects more explicitly, Table 6 presents regression estimates where the dependent variable is MOIC uplift (Exit MOIC – Interim MOIC) for fully realized deals. Across all specifications, deal tone maintains a consistently positive and statistically significant association with the dependent variable, all significant at the 1% level. In Model 1, the coefficient interim MOIC is 0.132, implying a positive association between the interim performance and future returns. The magnitude of the coefficient on interim MOIC decreases to 0.039 in Model 5, in which we add the report tone, which shows a positive statistically significant positive coefficient. If a GP's tone in a report is one standard deviation higher, equivalent to 0.36, this is associated with 0.24x higher future MOIC uplift. This numbers imply a difference of €21.4 million, assuming the mean invested capital of approximately €88 milion in our sample. In Models 3 to 5, we introduce fixed effects and a full set of control variables for key performance indicators such as EBITDA Margin Growth, which is positively and significantly associated with future returns at the 10% level. It seems that EBITDA margin improvements reflect stronger operational efficiency and profitability, translating into higher deal performance in the future. In Model 5, Sales Growth is also positively associated with future returns at the 5% level. Larger companies, proxied by the EV at entry, also show a statistically significant positive coefficient, implying better performance in the future. We do not find consistent results for any other financial metric.[16] Regarding fund characteristics, larger funds document statistically significant lower future returns at the 1% level. The negative impact of fund size on returns supports the notion of diseconomies of scale in private equity, where larger and older funds may struggle to find attractive opportunities or maintain their edge. Moreover, Fund Age, representing the number of years since the first investment of the fund, shows a significant negative relationship with future returns. This effect is also statistically significant at the 1% level.

In Model 5, the report tone is the largest coefficient among all variables included in the model. Altogether, this finding indicates a robust relationship between tone and deal outcomes, suggesting that higher deal tone is predictive of higher future returns, possibly due to tone reflecting investor optimism or confidence about a deal's prospects. These and all following findings are also robust to including the number of sentences per GP report in the analysis.

In Table 7, we replicate Table 6 but using realized, partially realized, and unrealized deals. For unrealized or partially realized deals, we use the latest reported NAV to approximate the exit MOIC. The results remain unchanged compared to Table 6. The rest of the paper restricts the sample to fully realized deals. The rationale for this analysis lies in the premise that assessing the relationship

[16] Untabulated analysis show similar results when restricting the sample to using annual data available as of 31 December.

between intermediary information - determined by GPs (and possibly their advisors) in the absence of market prices - and final outcomes should focus on realized deals, where final outcomes reflect genuine market prices outside GP discretion.[17]

The previous analysis aggregates all reports of an investment's life into a single dataset. In the next test, presented in Table 8, we refine this approach by re-running the same specification on yearly subsamples - examining intermediary data separately for each deal's first year, second year, and so forth, up to year five. Due to varying deal durations, documented above, the number of observations naturally decreases with each subsequent deal year.[18]

The results reveal that the coefficient on deal tone, while remaining highly statistically significant, diminishes over the course of a deal's life. For instance, for deals that persist to year five, the tone coefficient stands at 0.663, a 43% reduction from the 0.951 observed in the first year. Notably, this pattern holds true even when examining unreported beta coefficients. In contrast, the relationship between interim MOIC and future returns is only significant in years 2 and 3.

Our analysis indicates that tone serves primarily as a signal for future value creation potential, particularly in a deal's early stages when uncertainty is highest and growth opportunities remain substantial. The EBITDA margin growth coefficient becomes significant (0.339) in year 3, suggesting that profitability improvements emerge as return predictors midway through the holding period. This pattern corresponds with private equity's typical value creation timeline, where operational enhancements require time to manifest in financial results.

3.2. Robustness analysis

Our main analysis provides strong empirical results, which we validate through a set of robustness tests. These tests demonstrate that our findings are robust to the realization status of investments and alternative approaches to measuring both future success and tone.

To begin, Table 5 substitutes Exit MOIC – Interim MOIC with exit MOIC as the dependent variable in the same set of regressions (again using all deals). Exit MOIC serves as an alternative direct measure of future value development. Mechanically, interim MOIC shows a significant positive correlation with exit MOIC in nearly all regressions, suggesting that deals with higher interim performance are more successful exits. Crucially, FinBERT tone remains strongly correlated with

[17] Table A2 replicates Table 7 using Exit MOIC as the dependent variable.
[18] Table A3 replicates Table 8 using Exit MOIC as the dependent variable.

Exit MOIC, with a one-standard-deviation increase in tone (0.36 in our sample) being associated with a 0.639x higher exit MOIC.

Having established robustness to both sample inclusion and alternative performance measures, we also show that our findings hold when employing three alternative tone measures. Table 6 presents six specifications: three for the full sample of deals and three for the subsample of fully realized deals. In Models (1) and (4), we employ abnormal FinBERT tone, which confirm our primary findings. This measure isolates the portion of tone not attributable to past or current deal performance, reflecting a GP's judgment about future performance. To calculate abnormal FinBERT tone, we regress the raw FinBERT tone on all controls and fixed effects, using the residuals as the measure. Models (2) and (5) employ Financial-RoBERTa, an alternative language model trained and fine-tuned in the financial context. Like FinBERT, it classifies sentences as positive, negative, or neutral. While slightly weaker, its coefficient is still 0.538 and highly significant at the 1% level. Finally, in Columns (3) and (6), we use the Loughran and McDonald dictionary-based tone measure. The models yield highly significant coefficients of 6.776 and 7.568, respectively, for a one-unit increase in the ratio of positive words (in excess of negative words) over all words in the dictionary.[19]

Table 11 presents coefficients from OLS regressions with MOIC uplift as the dependent variable, using Report Tone and Interim MOIC as key explanatory variables, alongside other deal-level financial metrics and fund characteristics. Panel A demonstrates that our results remain robust to alternative FinBERT tone calculation methods. While our main analysis uses the mean sentiment score across all sentences in a report (where FinBERT classifies each sentence as negative (-1), neutral (0), or positive (1)), we find consistent results when using the median, excluding neutral sentences, omitting reports with fewer than five sentences, or incorporating standard deviation measures of sentiment variation.

Panel B of the table shows a remarkably consistent influence of interim report tone across subsamples split by investment type, GP experience, fund size, exit deal performance, and investment duration.

3.3. Fundraising

Our main analysis suggests that GPs strategically embed signals in their reports to compensate for potential biases in NAVs. A particularly relevant context for understanding this behavior is during the fundraising period, when GPs aim to raise a new fund using the same investment strategy. In this

[19] Table A4 replicates Table 9 using Exit MOIC as the dependent variable.

period, GPs face heightened scrutiny as Limited Partners (LPs) evaluate whether to reinvest capital. Accurate reporting becomes pivotal not only to demonstrate the performance of existing portfolios but also to maintain credibility and attract new commitments.

While prior studies have documented NAV inflation preceding fundraising efforts, the mechanisms underlying these patterns, as well as their effectiveness, remain contested (e.g., Barber and Yasuda, 2017; Brown et al., 2019). Reports generated during fundraising offer a unique opportunity to assess how GPs utilize textual narratives to enhance the perceived value of their portfolios. We hypothesize that GPs place greater emphasis on tone during fundraising periods, as these reports serve as a tool to influence LPs' evaluations and build confidence in future performance.

Table 12 evaluates the role of deal tone in predicting exit MOIC during fundraising periods. The dependent variable across all models is exit MOIC again, and the regressors include the set of characteristics used in the main analysis, as well as interaction terms between fundraising and both interim MOIC and deal tone (measured using FinBERT).

When assessing the model specification used in the previous analysis outside and during fundraising (Models 1 and 2, respectively), *Report Tone* is more informative for predicting exit MOIC when the private equity (PE) firm is actively fundraising, as indicated by the stronger coefficient (0.850) than when the PE firm is not actively raising capital (0.643). This suggests that the informational value of tone increases by approximately 13% (= 0.850 / 0.643) during fundraising periods, implying that PE firms may emphasize tone as a signal of prospects to attract investors. Conversely, we observe a weaker coefficient of Interim MOIC (-0.004) when PE firms are fundraising than when they are not (0.050).

The coefficient of the interaction between Report tone and Fundraising in Model 3 suggests that the informativeness of tone about future returns increases during the fundraising in line with the comparison between Models 1 and 2. On the other hand, the informativeness of interim MOIC on future performance decreases during the fundraising period a follow-on fund.

The final two columns replicate Model 3 across GP Experience subsamples. We split the sample at the median fund sequence of three, distinguishing between emerging managers (funds up to third generation) and established GPs (those beyond the third fund). Our analysis reveals that tone maintains consistent relevance outside fundraising periods across both subsamples, though its enhanced significance during fundraising is predominantly driven by more experienced GPs. Interim MOIC, conversely, displays divergent patterns conditional on fund sequence. For emerging managers, interim MOIC exhibits both economic and statistical significance outside fundraising periods, with no differential effect during fundraising. For established GPs, however, interim MOIC shows no significant relationship with MOIC uplift outside fundraising windows, but demonstrates significantly lower correlation during fundraising periods.

Overall, these findings highlight the strategic role of GP reports during fundraising periods. Deal tone is particularly informative during these times, serving as a tool for GPs to shape LP perceptions and emphasize future potential, while avoiding the explicit risk of later LP disappointment associated with inflating NAVs.

3.4 Deals Across Regions

Our sample also allows us to explore differences in the use of report tone and interim valuations across regions. Although our sample includes deals from all over the world, we constrained the deals to be in North America and Europe only to achieve better homogeneity. Splitting the deals across deal location in either Europe or North America leads to strikingly different results.

A striking pattern emerges in Table 13 when comparing European and North American deals. European investments consistently show positive coefficients for Interim MOIC across various subsamples and alternative measures of tone. In contrast, North American deals predominantly exhibit negative coefficients for Interim MOIC. The results are the same if we split the sample across GP location. These consistent differences highlight a significant regional variation in how Interim MOIC and Report Tone relate to future performance in private equity investments. The positive Interim MOIC coefficients in Europe versus the negative ones in North America suggest fundamentally different dynamics in these markets, potentially reflecting variations in valuation practices, market conditions, or reporting tendencies.

The results in Table 13 show that positive interim tone consistently predicts higher MOIC uplift across regions, but the relationship between interim valuation measures and final returns is the opposite for European and North American deals. The different influence of interim valuation measures contrast with the results in a recent concurrent paper (Ercan et al. (2024), which focuses on interim valuations and does not analyze tone. Our findings suggest that GPs around the world use positive tone in interim reports to signal good news, but do not do the same in terms of interim valuations. It is possible that the maturity of the market and the sophistication of LPs in both sides of the Atlantic are an important reason of the differences found.

4. Predicting future returns using Machine Learning

The evidence we provided so far suggests that GP reports do contain substantial amounts of relevant qualitative and quantitative information for investors, though the challenge seems not to lie in what is reported but in how it is presented and interpreted. If we are right with this interpretation, an investor accurately processing all the information provided in GP reports should be able to predict ultimate outcomes with reasonable accuracy. We mimic such an investor with machine learning algorithms. If they can learn the patterns, sophisticated investors can do it too. Hence, in this section, we explore the potential of machine learning to predict future deal returns by leveraging information from company-specific sections in GP reports.

Our setting involves a large number of variables that are not only high-dimensional but also highly correlated, presenting challenges for traditional econometric approaches. Machine learning offers a robust alternative, capable of identifying patterns and relationships that would otherwise remain undetected. To this end, we implement two widely used machine learning techniques: Lasso Regression: A linear model that applies a penalty to shrink less relevant coefficients to zero, making it well-suited for handling multicollinearity while retaining interpretability of coefficient estimates; and Random Forest (RF): A non-linear ensemble learning method that builds multiple decision trees and averages their outputs. While RF models are less interpretable, they excel in capturing complex, non-linear relationships among variables. These models are trained on the same set of variables included in Model 1 of Table 12.

We train these models to predict outperformance which is defined as a binary indicator capturing whether a deal outperformed relative to its peers with information available one year after investing in a company. To define outperformance, we benchmark each deal's MOIC uplift against the median gross MOIC uplift of the exit year. Additionally, we benchmark each deal's Exit MOIC against the median gross MOIC uplift of the exit year. The binary outperformance indicator takes the value of 1 if the deal exceeds the benchmark or threshold and 0 otherwise, allowing us to analyze both relative and absolute measures of success. In a second stage, we train models to predict MOIC uplift (i.e., a continuous variable) throughout the life of the deal.

To ensure robustness and avoid look-ahead bias, we implement a time-based split for training and testing the machine learning models. Specifically, for each year between 2011 and 2020, we train the algorithms on deals exited prior to the cut-off date and test them on deals initiated after the cut-off date. Deals in the test sample must be realized before June 2024. This temporal separation mirrors real-world conditions, where predictions rely solely on information available at the time of analysis, without knowledge of future outcomes.

To assess the predictive accuracy of the machine learning algorithms, we employ standard evaluation metrics widely used in the literature. For binary outperformance predictions, we use two complementary metrics: balanced accuracy and Area Under the Receiver Operating Characteristic Curve (ROC-AUC):

Balanced Accuracy: This metric accounts for class imbalances and is calculated as the average of the true positive rate $(TP/(TP + FP))$ and the true negative rate $(TN/(TN + FN))$. Balanced Accuracy ensures that the model's performance on both classes (outperforming and underperforming deals) is weighted equally:

$$Balanced\ accuracy: \frac{(TP + FP) + TN/(TN + FN)}{2}$$

Area Under the Receiver Operating Characteristic Curve (ROC-AUC): This metric evaluates the model's ability to discriminate between outperforming and underperforming deals. A model with perfect predictions achieves a ROC-AUC of 1, while a model with no predictive power scores 0.5, equivalent to random guessing. The ROC-AUC provides a holistic view of the model's classification performance across all decision thresholds.

4.1. Goodness of fit after one year of closing the deal

Table reports the results of machine learning models predicting private equity deal success one year after deal entry. Success is defined using two benchmarks: (1) MOIC uplift above the median for the exit year, and (2) Exit MOIC above the median for the exit year. The set of variables used to train the models include deal-level characteristics (e.g., Report tone, interim MOIC, Staleness Frequency, Markdown Frequency), firm-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth), and fund-level controls (e.g., fundraising status, Big Four Auditor, Fund Size, Fund Age). Fixed effects for industry, and region are included. The two models, Lasso Regression and Random Forest, demonstrate strong predictive accuracy across both benchmarks.

The performance metrics—Area Under the Curve (AUC) and Balanced Accuracy—highlight the models' effectiveness. Lasso and Random Forest present similar AUC and Accuracy scores for each benchmark. The goodness of fit is higher when algorithms are trained to predict the exit MOIC than when the MOIC uplift is the dependent variable. The economic impact of using these algorithms to predict future performance is relevant: deals predicted to outperform the median exit MOIC (MOIC uplift) delivered an average 3.34x exit MOIC (1.97x MOIC uplift) using Lasso. The deals predicted to underperform by the same algorithm delivered an average 1.70x exit MOIC (1.30x MOIC uplift).

The results highlight the potential of machine learning for predicting deal outcomes. These models enable Limited Partners (LPs) to better allocate resources and evaluate GP performance, while General Partners (GPs) can leverage these tools to identify high-potential deals and enhance reporting processes.

4.2. Predicting Exit MOIC Across Deal Years

In this section, we evaluate the economic performance of the two models in a more challenging task: predict exit MOIC over time using the same set of variables. Table 15 presents the MOIC uplift segmented by quartiles of machine learning (ML)-predicted exit MOIC. As in a classification setting, regression models can predict remarkably well an investment's final outcome.

Panel A of Table reports the average MOIC uplift for deals categorized into quartiles based on predictions from a Lasso regression model, which was trained on the same set of qualitative and quantitative variable that we use in our main analysis.

The difference in realized MOIC uplift based on Lasso predictions is economically substantial. Deals in the highest quartile of predicted outperformance deliver a mean average MOIC of 1.63x for the fund - nearly ten times higher than the 0.15x mean average MOIC observed for deals in the lowest quartile. Naturally, this difference is highly statistically significant.

To investigate whether GPs provide early indicators in their reports that could predict final outcomes, we analyze nascent investments. Even at the outset, one year (or two semesters) after the LBO or PE acquisition, the difference between the lowest and highest quartiles of Lasso predictions remains striking. Deals in the highest quartile deliver an average average MOIC of 2.02x, compared to only 0.04x in the lowest quartile - a significant difference of 1.98x, despite these deals being only one year old. This is noteworthy given that these firms, on average, remain a total of five years or ten semesters in PE ownership. However, it seems that the course is already set early on.

Panel B replicates these results using predictions from a random forest model to forecast exit MOICs instead of Lasso regression. The findings are remarkably consistent, indicating that our results are robust to different statistical methods for analyzing the information set.

Figure 1 presents the variables most relevant to predict exit MOIC using Lasso. The model is trained on deals exited before each year from 2011 to 2017 and applied to subsequent deals to predict MOIC uplift. Positive coefficients (in green) indicate variables that positively contribute to deal success, while negative coefficients (in red) indicate factors negatively associated with performance. Similar to what we observe in Table 13 using an OLS regression, we find that *Report tone* presents the largest positive coefficient, while Markdown Frequency has the largest negative coefficient among all variables. Fund Age, Realization Value, and Staleness frequency also present negative coefficients. Overall, the variables found to be important in predicting final performance are economically meaningful concepts and seem consistent with the existing literature.

5. Conclusion

Our paper provides the first analysis of the role of qualitative information in PE reporting. Our results highlight the strategic use of qualitative information by General Partners (GPs) to convey forward-looking insights about portfolio company performance. The analysis of nearly 20,000 reports, including over 600,000 sentences of commentary, demonstrates that textual Report tone - quantified using advanced machine learning models offers significant predictive power for final investment outcomes.

Our findings indicate that while Net Asset Value (NAV) figures serve as a baseline metric for assessing interim performance, the accompanying qualitative disclosures play a crucial role in addressing information asymmetries between GPs and Limited Partners (LPs). The predictive strength of tone is particularly evident in lower-performing investments, where textual signals compensate for biases in quantitative reporting, as well as during fundraising periods, when GPs seek to attract new capital. These insights align with the double agency framework, where GPs navigate competing incentives to balance the interests of LPs and external principals, such as pension fund trustees.

The implications of this study extend beyond private equity, offering broader lessons for financial reporting and market transparency. Our results underscore the importance of integrating qualitative data into performance evaluation frameworks and suggest that machine learning tools can play a vital role in extracting actionable insights from unstructured financial texts. For policymakers and investors, the findings advocate for greater scrutiny of both quantitative and qualitative disclosures, particularly in contexts where NAVs may not fully reflect the economic reality of underlying investments.

Ultimately, this study enriches our understanding of information dynamics in private equity and highlights the potential of textual analysis to unveil hidden patterns and biases in financial reporting, paving the way for more informed investment decisions and enhanced market efficiency.

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7. Tables and Figures

Table 1: Sample Construction

This table presents the progressive construction of the dataset, summarizing the sample of reports and deals at each stage. For each stage, the table reports the mean and median (P50) of Total Value (in million euros) and number of sentences. The table also includes summary statistics for deals, including the mean and median Exit MOIC (Multiple of Invested Capital), and the mean and median number of reports per deal. Percent changes between subsequent stages are shown for Total Value and Exit MOIC.

	Reports					Deals				
	Obs.	Total Value		Sentences		Obs.	Exit MOIC		Reports	
		Mean	P50	Mean	P50		Mean	P50	Mean	P50
1. Buyout, Other PE	25,103	195.8	57.9			1,932	2.26	1.91	12.4	12.0
2. Europe, North America	23,265	202.1	58.1			1,834	2.26	1.88	12.6	12.0
(2/1)	(93%)					(95%)				
3. Tone available	20,454	194.9	58.0	9.9	8.0	1,795	2.27	1.88	12.6	12.0
(3/2)	(88%)					(98%)				
4. Financials available	17,219	201.8	60.0	10.2	9.0	1,727	2.29	1.91	12.6	12.0
(4/3)	(84%)					(96%)				

Table 2: Reports and Deal Characteristics

This table provides descriptive statistics for report-level and deal-level characteristics. Panel A shows report-level statistics, including MOIC (Multiple of Invested Capital), qualitative information measures, financial metrics, and fund characteristics. Panel B shows deal-level statistics, focusing on Exit MOIC and Average Report Tone across investment types, regions, exit statuses, and investment durations. For each variable, the number of observations (N_Obs), mean, standard deviation (Std. Dev.), 25th percentile (p25), median, and 75th percentile (p75) are displayed.

Panel A: Semester-Level

		N_Obs	Mean	Std Dev.	p25	Median	p75
MOIC:							
1	Current	23,262	1.52	1.36	0.93	1.09	1.79
2	MOIC Uplift	21,431	0.66	1.64	-0.20	0.28	1.21
3	Staleness Frequency	21,431	0.43	0.30	0.20	0.40	0.60
4	Markdown Frequency	21,431	0.29	0.25	0.00	0.27	0.46
5	Realization Share	23,262	0.17	0.31	0.00	0.00	0.18
Qualitative Information:							
5	Report Tone	20,454	0.23	0.36	0.00	0.25	0.50
6	Tone [FinRoBERTa]	20,454	0.30	0.36	0.00	0.31	0.53
7	Tone [LM Dictionary]	18,772	0.00	0.02	-0.01	0.00	0.02
8	Number of Sentences	20,454	9.91	7.98	4.00	8.00	13.00
Financial metrics:							
9	Sales	17,219	733.46	1,366.80	52.80	170.00	650.00
10	EBITDA Margin	17,219	0.18	0.14	0.09	0.15	0.24
11	EBITDA Valuation Multiple	17,219	9.01	5.14	6.21	8.29	11.07
12	Debt/EV	17,219	0.59	0.27	0.40	0.61	0.80
Fund Characteristics:							
13	Fundraising	23,262	0.15	0.36	0.00	0.00	0.00
14	Fund Age [years]	23,262	5.67	2.97	3.00	5.00	8.00
15	Fund Generation	23,262	4.11	2.26	2.00	4.00	5.00
16	Big Four Auditor	23,262	0.91	0.29	1.00	1.00	1.00

Panel B: Deal-Level

		Exit MOIC			Average Report Tone	
		N_Obs	Mean	Std Dev.	Mean	Std. Dev
Investment type:						
1	Buyout	1,547	2.22	2.08	0.23	0.36
2	Other PE	248	2.56	3.00	0.27	0.35
Region:						
3	Europe	1,259	2.24	2.23	0.20	0.35
4	North America	536	2.34	2.22	0.32	0.37
Exit status:						
8	Unrealized	229	0.61	1.10	0.14	0.37
9	Partially realized	186	2.13	2.23	0.25	0.38
10	Realized	1,380	2.57	2.24	0.25	0.35
Investment duration						
8	0 to 2 years	155	2.38	2.28	0.24	0.37
9	2 to 3 years	194	2.50	2.08	0.23	0.34
10	3 to 4 years	246	2.73	2.33	0.28	0.35
11	4 to 5 years	276	2.41	2.14	0.24	0.35
11	5 to 6 years	247	2.22	1.96	0.24	0.36
11	≥6 years	677	1.97	2.31	0.22	0.37

Table 3: Main Variables Across Deal Years (By Deal Duration) for fully realized deals

This table examines key metrics over the lifecycle of private equity deals, categorized by deal duration and deal age (in years). Panel A presents the Interim MOIC (Multiple of Invested Capital), Panel B presents the Report Tone (FinBERT), and Panel C presents the Realization Share (fraction of total deal value that has been realized). Deal duration is segmented into six groups (<2 years, 2–3 years, ..., >6 years), with deal age spanning from entry year through year 6 and beyond (>6 years). For each combination of deal duration and deal age, mean values are presented, along with overall totals for each column and row.

Panel A: Interim MOIC

Deal duration:	Deal Age (years)							
	Entry	**1**	**2**	**3**	**4**	**5**	**6**	**6<**
< 2 yrs.	1.00	2.10	2.83					
2 – 3 yrs.	1.00	1.48	2.03	3.13				
3 – 4 yrs.	1.00	1.25	1.55	2.06	2.85			
4 – 5 yrs.	1.00	1.23	1.48	1.79	2.15	2.54		
5 – 6 yrs.	1.00	1.17	1.34	1.54	1.72	2.02	2.44	
> 6 yrs.	1.00	1.17	1.31	1.42	1.54	1.70	1.87	1.86

Panel B: Report Tone

Deal duration:	Deal Age (years)							
	Entry	**1**	**2**	**3**	**4**	**5**	**6**	**6<**
< 2 yrs.	0.26	0.25	0.24					
2 – 3 yrs.	0.30	0.27	0.28	0.27				
3 – 4 yrs.	0.29	0.29	0.31	0.31	0.29			
4 – 5 yrs.	0.25	0.23	0.19	0.26	0.30	0.26		
5 – 6 yrs.	0.28	0.26	0.24	0.27	0.28	0.28	0.26	
> 6 yrs.	0.23	0.24	0.19	0.22	0.24	0.24	0.22	0.21

Panel C: Realization Share

Deal duration:	Deal Age (years)							
	Entry	**1**	**2**	**3**	**4**	**5**	**6**	**6<**
< 2 yrs.	0.01	0.28	1.00					
2 – 3 yrs.	0.00	0.02	0.11	1.00				
3 – 4 yrs.	0.01	0.04	0.09	0.15	1.00			
4 – 5 yrs.	0.00	0.03	0.09	0.16	0.23	0.99		
5 – 6 yrs.	0.00	0.03	0.07	0.09	0.14	0.22	1.00	
> 6 yrs.	0.00	0.04	0.07	0.10	0.13	0.17	0.22	0.42

Table 4: Correlation Matrix

This table presents the pairwise correlations among key variables used in the analysis. The variables include metrics related to deal performance (e.g., Interim MOIC, Gross Up, Staleness, Markdown, Realization), tone measures (e.g., FinBERT, FinRoBERTa, Dictionary LM), and financial metrics (e.g., Sales, EBITDA, D/EV). The correlation coefficients highlight the relationships between performance outcomes, tone measures, and firm-level financial indicators. ^{c}, ^{b}, and ^{a} denote statistical significance at the 10%, 5%, and 1% level, respectively.

		1	2	3	4	5	6	7	8	9	10	11	12
1	Interim MOIC												
2	MOIC Uplift	-0.03^{a}											
3	Staleness Frequency	-0.11^{a}	0.05^{a}										
4	Markdown Frequency	-0.33^{a}	-0.15^{a}	-0.26^{a}									
5	Realization Share	0.29^{a}	-0.06^{a}	-0.09^{a}	-0.01^{c}								
6	FinBERT	0.13^{a}	0.13^{a}	-0.02^{b}	-0.21^{a}	-0.04^{a}							
7	FinRoBERTa	0.12^{a}	0.11^{a}	-0.02^{a}	-0.19^{a}	-0.04^{a}	0.82^{a}						
8	Dictionary (LM 2011)	0.12^{a}	0.09^{a}	-0.02^{b}	-0.16^{a}	-0.02^{a}	0.60^{a}	0.56^{a}					
9	Number of Sentences	-0.11^{a}	-0.03^{a}	0.05^{a}	0.05^{a}	-0.09^{a}	-0.03^{a}	-0.03^{a}	-0.01^{c}				
10	Sales	0.14^{a}	-0.00	-0.12^{a}	-0.01	0.18^{a}	0.13^{a}	0.12^{a}	0.07^{a}	0.10^{a}			
11	EBITDA Margin	0.13^{a}	-0.00	0.02^{b}	-0.15^{a}	0.06^{a}	0.10^{a}	0.09^{a}	0.03^{a}	-0.05^{a}	-0.02^{a}		
12	EBITDA Valuation Multiple	0.09^{a}	-0.02^{a}	-0.02^{a}	-0.01^{c}	0.03^{a}	0.08^{a}	0.07^{a}	0.05^{a}	-0.01	0.09^{a}	-0.05^{a}	
13	D/EV	0.07^{a}	0.01	0.00	-0.05^{a}	-0.02^{a}	0.03^{a}	0.03^{a}	0.02^{b}	-0.04^{a}	-0.06^{a}	-0.02^{b}	-0.01^{c}

Table 5: MOIC uplift and MOIC variation across Tone categories

This table reports details on MOIC uplift (Exit MOIC – Interim MOIC) and MOIC variation (Mark-up, Stale, Mark-down) compared to the next report (t+1) across categories of tone (Positive, Neutral, Negative). For each tone category we show the percentage of observations falling into each MOIC variation category, the mean MOIC variation compared to the next report, and the mean MOIC uplift [c], [b], and [a] denote statistical significance at the 10%, 5%, and 1% level, respectively. T-tests are used to assess significance. Definitions of all the variables are provided in Appendix Table A1.

	MOIC variation To Next Report (t+1)				**Exit MOIC – Interim MOIC** (Mean)
	Categories			MOIC variation to t+1 (Mean)	
	Mark-up	Stale	Mark-down		
Tone (t)					
Positive	44.5%	36.6%	18.9%	0.16	0.83[a]
Neutral	33.7%	41.9%	24.4%	0.08	0,56
Negative	25.1%	37.0%	37.9%	-0.03	0,31
Total	39,6%	37.4%	23.0%	0.12	0.70

Table 6: Drivers of MOIC uplift

This table presents regression results analyzing the determinants of MOIC uplift (Exit MOIC – Interim MOIC) at the deal level for fully realized deals. The dependent variable in all models is MOIC uplift. Key explanatory variables include measures of Report Tone, interim MOIC, deal-level financial metrics (e.g., sales growth, margin growth), and fund characteristics (e.g., fund size and age). The table includes fixed effects for semester, investment year, industry, and region as indicated. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)
			Exit MOIC – Interim MOIC		
Report Tone		0.686[a]	0.669[a]	0.620[a]	0.677[a]
		(0.041)	(0.043)	(0.043)	(0.043)
Interim MOIC	0.132[a]	0.092[a]	0.078[a]	0.048[a]	0.039[a]
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
LN Sales Growth			0.082	0.106[c]	0.134[b]
			(0.064)	(0.063)	(0.063)
EBITDA Margin Growth			0.041[c]	0.038[c]	0.038[c]
			(0.022)	(0.022)	(0.022)
Valuation Growth			0.045[b]	0.032[c]	0.026
			(0.018)	(0.018)	(0.018)
LN EV at Entry			-0.020[b]	0.015[c]	0.069[a]
			(0.009)	(0.009)	(0.011)
Realization Value			-0.037	-0.027	0.016
			(0.073)	(0.072)	(0.072)
GP Fundraising? [0/1]			-0.051	-0.058	-0.043
			(0.041)	(0.042)	(0.042)
Year-end Report? [0/1]			0.012	0.031	-0.008
			(0.030)	(0.030)	(0.030)
Big Four Auditor? [0/1]			0.180[a]	0.182[a]	0.170[a]
			(0.062)	(0.063)	(0.062)
LN Fund Size (EURmn)					-0.117[a]
					(0.017)
Fund Generation					0.001
					(0.008)
Fund Age					-0.090[a]
					(0.010)
Constant	0.631[a]	0.524[a]	0.678[a]	0.070	1.963[a]
	(0.024)	(0.025)	(0.168)	(0.172)	(0.276)
Observations	15,070	15,070	12,998	12,998	12,998
Semester FE	YES	YES	YES	YES	YES
Investment Year FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Region FE	NO	NO	NO	YES	YES
Adj. R-squared	0.044	0.062	0.061	0.090	0.101

Table 7: Drivers of MOIC uplift (Realized, partially realized, and unrealized deals)

This table presents regression results analyzing the determinants of MOIC uplift (Exit MOIC – Interim MOIC) for all deals in sample. The dependent variable in all models is MOIC uplift. Key explanatory variables include measures of Report Tone, interim MOIC, deal-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth, Valuation Growth), and fund characteristics (e.g., fund size and age). The table includes fixed effects for semester, investment year, industry, and region as indicated. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)
			Exit MOIC – Interim MOIC		
Report Tone		0.596[a]	0.580[a]	0.545[a]	0.596[a]
		(0.035)	(0.037)	(0.037)	(0.037)
Interim MOIC	0.098[a]	0.065[a]	0.054[a]	0.038[a]	0.030[b]
	(0.012)	(0.012)	(0.013)	(0.013)	(0.012)
LN Sales Growth			0.054	0.074	0.094[c]
			(0.053)	(0.053)	(0.053)
EBITDA Margin Growth			0.048[b]	0.046[b]	0.047[b]
			(0.021)	(0.021)	(0.021)
Valuation Growth			0.032[b]	0.020	0.018
			(0.015)	(0.015)	(0.015)
LN EV at Entry			-0.002	0.019[b]	0.066[a]
			(0.008)	(0.008)	(0.010)
Realization Value			0.047	0.022	0.065
			(0.064)	(0.064)	(0.063)
GP Fundraising? [0/1]			-0.042	-0.050	-0.044
			(0.036)	(0.037)	(0.037)
Year-end Report? [0/1]			0.004	0.009	-0.024
			(0.026)	(0.026)	(0.026)
Big Four Auditor? [0/1]			0.166[a]	0.189[a]	0.189[a]
			(0.049)	(0.050)	(0.049)
LN Fund Size (EURmn)					-0.098[a]
					(0.015)
Fund Generation					-0.003
					(0.007)
Fund Age					-0.082[a]
					(0.009)
Constant	0.561[a]	0.464[a]	0.312[b]	-0.073	1.540[a]
	(0.021)	(0.021)	(0.145)	(0.151)	(0.246)
Observations	19,096	19,096	16,472	16,472	16,472
Semester FE	YES	YES	YES	YES	YES
Investment Year FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Region FE	NO	NO	NO	YES	YES
Adj. R-squared	0.045	0.059	0.057	0.078	0.087

Table 8: Drivers of MOIC uplift by Investment Age

This table presents regression results analyzing the determinants of MOIC uplift (Exit MOIC – Interim MOIC) for fully realized deals across five years following deal start. The analysis is clustered at the portfolio firm level, with separate regressions conducted for each year. Explanatory variables include Report Tone, Interim MOIC, deal-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth, Valuation Growth), and fund-level factors (e.g., Fundraising, Big Four Auditor, Fund Size, Fund Generation, and Fund Age). Fixed effects for semester, industry, and region are included. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)
	Exit MOIC – Interim MOIC				
	Year 1	Year 2	Year 3	Year 4	Year 5
Report Tone	0.951[a]	0.622[a]	0.848[a]	0.574[a]	0.663[a]
	(0.121)	(0.109)	(0.107)	(0.111)	(0.111)
Interim MOIC	0.156[b]	0.149[a]	0.033	0.029	-0.010
	(0.074)	(0.044)	(0.037)	(0.034)	(0.032)
LN Sales Growth	-0.039	0.271	0.162	0.411	0.404
	(0.099)	(0.169)	(0.195)	(0.264)	(0.308)
EBITDA Margin Growth	0.236	0.001	0.321[a]	0.068	-0.069
	(0.196)	(0.027)	(0.103)	(0.390)	(0.567)
Valuation Growth	-0.017	0.000	0.020	0.067	0.147[b]
	(0.038)	(0.042)	(0.046)	(0.052)	(0.059)
LN EV at Entry	0.091[a]	0.087[a]	0.080[a]	0.070[b]	0.021
	(0.029)	(0.027)	(0.028)	(0.028)	(0.029)
Realization Value	0.245	-0.187	0.004	-0.052	0.002
	(0.385)	(0.230)	(0.186)	(0.171)	(0.167)
GP Fundraising? [0/1]	0.303[a]	0.057	-0.166[c]	-0.218[b]	-0.195
	(0.105)	(0.090)	(0.095)	(0.107)	(0.121)
Year-end Report? [0/1]	-0.059	-0.037	0.012	-0.053	-0.007
	(0.079)	(0.074)	(0.074)	(0.076)	(0.077)
Big Four Auditor? [0/1]	0.242	0.224	0.186	0.088	0.159
	(0.179)	(0.167)	(0.160)	(0.152)	(0.155)
LN Fund Size (EURmn)	-0.136[a]	-0.120[a]	-0.152[a]	-0.133[a]	-0.139[a]
	(0.044)	(0.041)	(0.041)	(0.042)	(0.044)
Fund Generation	-0.016	0.009	0.011	0.021	0.023
	(0.022)	(0.020)	(0.020)	(0.021)	(0.021)
Fund Age	-0.149[a]	-0.119[a]	-0.107[a]	-0.075[a]	-0.037
	(0.028)	(0.026)	(0.026)	(0.027)	(0.029)
Constant	2.156[a]	1.707[b]	2.498[a]	2.130[a]	2.756[a]
	(0.750)	(0.689)	(0.682)	(0.701)	(0.711)
Observations	2,666	2,496	2,203	1,797	1,359
Adj. R-squared	0.0946	0.0828	0.0953	0.0757	0.0690

Table 5: Exit MOIC

This table presents regression results analyzing the determinants of Exit MOIC for fully realized deals. The dependent variable in all models is Exit MOIC. Key explanatory variables include Report Tone, Interim MOIC, deal-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth), and fund-level factors (e.g., Fundraising, Big Four Auditor, Fund Size, Fund Generation, and Fund Age). Fixed effects for semester, industry, and region are included as indicated. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)
			Exit MOIC		
Report Tone		0.682[a]	0.636[a]	0.586[a]	0.639[a]
		(0.039)	(0.041)	(0.041)	(0.041)
Interim MOIC	1.089[a]	1.052[a]	1.060[a]	1.036[a]	1.026[a]
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
LN Sales Growth			0.098	0.118[c]	0.147[b]
			(0.061)	(0.061)	(0.061)
EBITDA Margin Growth			0.041[c]	0.038[c]	0.038[c]
			(0.021)	(0.021)	(0.021)
Valuation Growth			0.040[b]	0.028[c]	0.023
			(0.017)	(0.017)	(0.017)
LN EV at Entry			-0.011	0.020[b]	0.072[a]
			(0.008)	(0.008)	(0.010)
Realization Value			-0.325[a]	-0.349[a]	-0.306[a]
			(0.053)	(0.053)	(0.052)
GP Fundraising? [0/1]			-0.044	-0.050	-0.038
			(0.040)	(0.040)	(0.040)
Year-end Report? [0/1]			0.009	0.025	-0.011
			(0.028)	(0.028)	(0.028)
Big Four Auditor? [0/1]			0.157[a]	0.160[a]	0.152[b]
			(0.059)	(0.059)	(0.059)
LN Fund Size (EURmn)					-0.109[a]
					(0.016)
Fund Generation					-0.001
					(0.008)
Fund Age					-0.084[a]
					(0.009)
Constant	0.636[a]	0.532[a]	0.571[a]	0.032	1.797[a]
	(0.022)	(0.023)	(0.157)	(0.162)	(0.260)
Observations	16,064	16,064	13,839	13,839	13,839
Semester FE	YES	YES	YES	YES	YES
Investment Year FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Region FE	NO	NO	NO	YES	YES
Adj. R-squared	0.347	0.359	0.392	0.409	0.416

Table 6: Alternative Measures of Tone

This table presents regression results analyzing the determinants of MOIC uplift (Exit MOIC – Interim MOIC) for fully realized deals using alternative qualitative measures. The models evaluate "All Deals" and "Realized Deals" using three deal tone measures: Abnormal FinBERT tone, FinRoBERTa tone, and Dictionary-based tone (Loughran-McDonald 2011). Abnormal FinBERT tone is the residual of regressing FinBERT on performance metrics (e.g., Interim MOIC), deal-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth), fund-level controls (e.g., Fund Size, Fund Age), and fixed effects. Fixed effects for semester, industry, and region are included. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Exit MOIC – Interim MOIC					
	All Deals			Fully realized Deals		
	Abnormal FinBERT	FinRoBERTa	Dictionary LM 2011	Abnormal FinBERT	FinRoBERTa	Dictionary LM 2011
Report Tone	0.496[a]	0.486[a]	6.776[a]	0.569[a]	0.538[a]	7.568[a]
	(0.035)	(0.035)	(0.593)	(0.042)	(0.041)	(0.695)
Interim MOIC	1.050[a]	1.028[a]	1.038[a]	1.059[a]	1.034[a]	1.045[a]
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)	(0.014)
LN Sales Growth	0.144[a]	0.108[b]	0.125[b]	0.197[a]	0.160[a]	0.186[a]
	(0.051)	(0.051)	(0.054)	(0.061)	(0.061)	(0.065)
EBITDA Margin Growth	0.046[b]	0.047[b]	0.044[b]	0.037[c]	0.037[c]	0.034
	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.022)
Valuation Growth	0.019	0.017	0.013	0.026	0.025	0.017
	(0.014)	(0.014)	(0.015)	(0.017)	(0.017)	(0.018)
LN EV at Entry	0.069[a]	0.067[a]	0.071[a]	0.073[a]	0.072[a]	0.074[a]
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)
Realization Value	-0.262[a]	-0.194[a]	-0.154[a]	-0.401[a]	-0.327[a]	-0.286[a]
	(0.047)	(0.047)	(0.052)	(0.052)	(0.052)	(0.059)
GP Fundraising? [0/1]	-0.031	-0.033	-0.017	-0.031	-0.033	-0.032
	(0.035)	(0.035)	(0.037)	(0.040)	(0.040)	(0.041)
Year-end Report? [0/1]	-0.014	-0.019	-0.020	-0.001	-0.007	-0.007
	(0.025)	(0.025)	(0.026)	(0.028)	(0.028)	(0.030)
Big Four Auditor? [0/1]	0.159[a]	0.176[a]	0.193[a]	0.137[b]	0.161[a]	0.165[a]
	(0.047)	(0.047)	(0.049)	(0.059)	(0.059)	(0.062)
LN Fund Size (EURmn)	-0.065[a]	-0.084[a]	-0.082[a]	-0.081[a]	-0.100[a]	-0.095[a]
	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.017)
Fund Generation	-0.002	-0.005	-0.001	0.002	-0.002	0.000
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Fund Age	-0.075[a]	-0.077[a]	-0.076[a]	-0.082[a]	-0.084[a]	-0.082[a]
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
Constant	0.932[a]	1.219[a]	1.196[a]	1.283[a]	1.576[a]	1.507[a]
	(0.230)	(0.231)	(0.241)	(0.258)	(0.260)	(0.273)
Observations	17,541	17,541	16,317	13,839	13,839	12,842
Adj. R-squared	0.410	0.410	0.391	0.413	0.413	0.391

Table 11: Robustness (Realized deals only)

This table presents coefficients from OLS regressions where MOIC uplift is the dependent variable, with Report Tone and Interim MOIC as key explanatory variables, alongside other deal-level financial metrics and fund characteristics. The dependent variable in all models is MOIC uplift. Independent variables include deal-level characteristics (e.g., Report Tone, Interim MOIC), firm-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth), fund-level controls (e.g., Fund Generation, Fund Size), and fixed effects. Fixed effects for semester, industry, and region are included. Robust standard errors are reported in parentheses, and [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

Panel A: Alternative measures of Tone

	All Deals		
Alternative measures	Tone	Interim MOIC	Obs
Tone - Median	0.375[a]	0.051[a]	12,320
	(0.029)	(0.015)	
Tone excluding neutral sentences	0.409[a]	0.022	11,851
	(0.029)	(0.016)	
Tone excluding reports with less than 5 sentences	0.761[a]	-0.028	10,496
	(0.053)	(0.017)	
Tone - Standard Deviation	-0.152[b]	0.069[a]	12,190
	(0.065)	(0.015)	

Panel B: Subsample analysis

	All Deals		
Groups	Tone	Interim MOIC	Obs
Investment type			
Buyout	0.625[a]	0.079[a]	11,366
	(0.041)	(0.014)	
Other PE	1.011[a]	-0.152[a]	1,632
	(0.192)	(0.052)	
GP experience			
Fund sequence ≤2	0.537[a]	0.038	3,432
	(0.092)	(0.033)	
Fund sequence >3	0.683[a]	0.037[b]	9,563
	(0.049)	(0.016)	
Fund Size			
Fund size ≤EUR 1bn	0.730[a]	0.076[a]	7,285
	(0.064)	(0.022)	
Fund size >EUR 1bn	0.662[a]	-0.021	5,713
	(0.057)	(0.018)	
Exit Deal performance			
Exit MOIC ≤1x	0.081[a]	-0.923[a]	4,036
	(0.014)	(0.007)	
Exit MOIC >3x	0.227[c]	-0.354[a]	3,358
	(0.117)	(0.030)	
Investment duration			
Investment duration ≤3 years	1.144[a]	0.118[b]	1,060
	(0.145)	(0.052)	
Investment duration >3 years	0.629[a]	0.038[b]	11,937
	(0.045)	(0.015)	

Table 12: Fundraising Analysis (Realized deals only)

This table presents regression results analyzing the determinants of MOIC uplift (Exit MOIC – Interim MOIC) when funds are raising a next fund during the reporting period. The analysis includes subsample regressions for funds below and above the median fund sequence, respectively. Key independent variables include Report Tone, Interim MOIC, and interaction terms such as Report Tone*Fundraising and Interim MOIC*Fundraising. Deal-level financial metrics (e.g., Sales Growth , Realization Status) and fund-level controls (e.g., Fund Size, Fund Age) are included. Fixed effects for semester, industry, and region are included. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)
	Exit MOIC – Interim MOIC				
	Fundraising period		All	Fund Sequence	
	Outside	During		<= 3	> 3
Report Tone	0.643[a]	0.850[a]	0.634[a]	0.592[a]	0.616[a]
	(0.048)	(0.107)	(0.048)	(0.066)	(0.074)
Report Tone*Fundraising			0.228[b]	0.195	0.300[b]
			(0.106)	(0.153)	(0.153)
Interim MOIC	0.050[a]	-0.004	0.049[a]	0.133[a]	0.015
	(0.016)	(0.038)	(0.016)	(0.022)	(0.024)
Interim MOIC*Fundraising			-0.058	0.019	-0.104[b]
			(0.036)	(0.052)	(0.051)
Fundraising		-0.060	-0.093	-0.128	0.108
		(0.102)	(0.091)	(0.098)	(0.096)
LN Sales Growth	0.095	0.232	0.132[b]	0.126	0.006
	(0.070)	(0.146)	(0.063)	(0.089)	(0.090)
EBITDA Margin Growth	0.040[c]	0.230	0.038[c]	0.021	0.355[a]
	(0.022)	(0.332)	(0.022)	(0.022)	(0.106)
Valuation Growth	0.024	0.057	0.026	0.003	-0.002
	(0.020)	(0.041)	(0.018)	(0.008)	(0.010)
LN EV at Entry	0.061[a]	0.092[a]	0.070[a]	-0.022	-0.019
	(0.012)	(0.027)	(0.011)	(0.017)	(0.017)
Realization Value	0.001	0.061	0.013	-0.050	0.140
	(0.077)	(0.199)	(0.072)	(0.100)	(0.109)
Big Four Auditor? [0/1]	0.039	0.472[a]	0.166[a]	-0.169[b]	0.724[a]
	(0.072)	(0.136)	(0.062)	(0.085)	(0.103)
LN Fund Size (EURmn)	-0.104[a]	-0.130[a]	-0.117[a]	-0.012	-0.004
	(0.019)	(0.041)	(0.017)	(0.027)	(0.027)
Fund Generation	-0.004	0.010	0.001	-0.112[a]	0.022
	(0.009)	(0.020)	(0.008)	(0.035)	(0.013)
Fund Age	-0.083[a]	-0.227[a]	-0.090[a]	-0.137[a]	-0.034[a]
	(0.011)	(0.035)	(0.010)	(0.014)	(0.016)
Constant	1.940[a]	2.273[a]	1.965[a]	1.061[a]	2.812[a]
	(0.305)	(0.703)	(0.277)	(0.326)	(0.683)
Observations	10,464	2,531	12,998	8,549	4,449
Adj. R-squared	0.0952	0.133	0.101	0.126	0.0983

Table 13: Europe versus North America (Realized deals only)

This table presents regression results analyzing the determinants of MOIC uplift (Exit MOIC – Interim MOIC) across Europe and North America based on the geographic focus of the fund, the location of the portfolio companies, and the location of the Private Equity Firm. The dependent variable in all models is MOIC uplift. Independent variables include Report Tone, Interim MOIC, deal-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth), and fund-level factors (e.g., Fundraising, Big Four Auditor, Fund Size, Fund Generation, and Fund Age). Fixed effects for semester, industry, and region are included. Robust standard errors are reported in parentheses, and ^{a}, ^{b}, and ^{c} denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Exit MOIC – Interim MOIC				
	All	Fund Region		Portfolio Company country			Accounting guidelines		
		Europe	North America	Civil Law	Common Law	Common Law (excl. US)	IFRS	GAAP	GAAP (excl. US GAAP)
Report Tone	0.529^{a}	0.500^{a}	0.504^{a}	0.543^{a}	0.449^{a}	0.727^{a}	0.533^{a}	0.475^{a}	0.526^{a}
	(0.037)	(0.046)	(0.065)	(0.047)	(0.063)	(0.106)	(0.097)	(0.043)	(0.068)
Interim MOIC	-0.022	0.042^{b}	-0.124^{a}	0.068^{a}	-0.150^{a}	-0.334^{a}	-0.163^{a}	-0.025^{c}	0.046^{c}
	(0.013)	(0.016)	(0.024)	(0.017)	(0.022)	(0.041)	(0.045)	(0.015)	(0.024)
MOIC Staleness Frequency	0.055	0.124^{b}	-0.221^{b}	0.171^{a}	-0.242^{a}	-0.478^{a}	0.094	0.038	0.385^{a}
	(0.047)	(0.056)	(0.087)	(0.058)	(0.081)	(0.117)	(0.128)	(0.055)	(0.083)
Markdown Frequency	-0.684^{a}	-0.474^{a}	-1.027^{a}	-0.369^{a}	-1.197^{a}	-1.335^{a}	-0.244	-0.846^{a}	-0.733^{a}
	(0.059)	(0.070)	(0.110)	(0.073)	(0.103)	(0.151)	(0.158)	(0.069)	(0.104)
LN Sales Growth	0.053	0.022	0.088	-0.035	0.187^{c}	-0.311^{c}	0.454^{a}	0.004	-0.265^{a}
	(0.053)	(0.062)	(0.102)	(0.062)	(0.099)	(0.159)	(0.138)	(0.063)	(0.093)
EBITDA Margin Growth	0.051^{b}	0.200^{b}	0.031	0.208	0.021	0.226^{c}	-0.536	0.053^{b}	0.339^{c}
	(0.021)	(0.099)	(0.026)	(0.163)	(0.023)	(0.123)	(0.567)	(0.022)	(0.182)
Valuation Growth	0.002	-0.048^{a}	0.107^{a}	-0.060^{a}	0.108^{a}	-0.033	-0.055	0.022	-0.039
	(0.015)	(0.018)	(0.026)	(0.019)	(0.024)	(0.035)	(0.037)	(0.017)	(0.027)
LN EV at Entry	0.070^{a}	0.098^{a}	0.049^{a}	0.060^{a}	0.086^{a}	-0.049^{c}	0.172^{a}	0.084^{a}	0.129^{a}
	(0.010)	(0.012)	(0.016)	(0.012)	(0.016)	(0.028)	(0.029)	(0.011)	(0.020)
Realization Value	0.100	0.241^{a}	-0.206^{c}	0.169^{b}	0.045	0.425^{b}	0.175	0.121^{c}	0.227^{c}
	(0.063)	(0.076)	(0.114)	(0.080)	(0.103)	(0.166)	(0.167)	(0.072)	(0.119)
Raising Next Fund? [0/1]	-0.052	-0.053	-0.036	-0.012	-0.102	-0.272^{a}	-0.024	-0.071^{c}	-0.100
	(0.037)	(0.044)	(0.068)	(0.046)	(0.062)	(0.099)	(0.101)	(0.041)	(0.066)
Big Four Auditor? [0/1]	0.162^{a}	-0.186^{a}	0.534^{a}	-0.099	0.492^{a}	0.998^{a}	-0.392^{b}	0.230^{a}	0.076
	(0.049)	(0.066)	(0.080)	(0.062)	(0.086)	(0.201)	(0.178)	(0.054)	(0.084)
LN Fund Size (EURmn)	-0.093^{a}	-0.054^{a}	-0.154^{a}	-0.026	-0.119^{a}	-0.084^{c}	-0.416^{a}	-0.112^{a}	-0.214^{a}
	(0.015)	(0.018)	(0.030)	(0.019)	(0.027)	(0.044)	(0.074)	(0.017)	(0.031)
Fund Generation	-0.002	-0.047^{a}	0.016	-0.056^{a}	0.018^{c}	0.082^{a}	-0.015	-0.009	0.012
	(0.007)	(0.011)	(0.010)	(0.011)	(0.009)	(0.015)	(0.022)	(0.008)	(0.016)
Fund Age	-0.080^{a}	-0.134^{a}	-0.004	-0.129^{a}	-0.019	0.138^{a}	-0.104^{a}	-0.076^{a}	-0.077^{a}
	(0.009)	(0.010)	(0.016)	(0.011)	(0.015)	(0.024)	(0.023)	(0.010)	(0.015)
Constant	1.634^{a}	0.925^{a}	2.946^{a}	0.935^{a}	1.624^{a}	1.834^{b}	6.662^{a}	1.857^{a}	2.852^{a}
	(0.250)	(0.291)	(0.604)	(0.307)	(0.483)	(0.770)	(1.475)	(0.287)	(0.501)
Observations	16,472	10,633	5,837	10,090	6,380	2,546	1,685	12,988	5,971
Adj. R-squared	0.0952	0.105	0.110	0.106	0.111	0.129	0.103	0.101	0.0953

Table 14: Machine Learning Prediction of MOIC uplift and Exit MOIC (First Deal Year Intermediary Info)

This table evaluates the out-of-sample goodness of fit of predictive models trained on deals exited before each year from 2011 to 2020 and then used to predict the MOIC uplift and exit MOIC of deals invested in that year, using Lasso regression and Random Forest algorithms to predict deal success. Success is measured by benchmarking the MOIC uplift and exit MOIC of each deal against those exited in the same year. Model performance metrics include Area Under the Curve (AUC) and Balanced Accuracy. The number of deals predicted as successful and their corresponding average MOIC uplift and Exit MOIC, and the number of deals with data are reported. Definitions of all the variables are provided in Appendix Table A1.

	Above the median MOIC Uplift		Above the median Exit MOIC	
	Lasso	**Random Forest**	**Lasso**	**Random Forest**
Area Under Curve	0,67	0,69	0,75	0,72
Balanced Accuracy	0,63	0,64	0,69	0,65
Companies predicted to outperform	125	122	142	139
Average MOIC uplift	1,97	1,92	3,34	3,26
Companies predicted to underperform	120	123	103	106
Average MOIC uplift	1,30	1,37	1,70	1,85

Table 15: Machine Learning Prediction of MOIC uplift Categories by Investment Age

This table evaluates predicted MOIC uplift quartiles based on machine learning models. Predictions are generated using Lasso Regression (Panel A) and Random Forest Regression (Panel B). Models are trained on deals exited before each year from 2011 to 2020 and applied to subsequent deals to predict Exit MOIC. The table shows the mean Exit MOIC for each predicted quartile (Lowest, 3rd, 2nd, Highest) and the High-Low difference (absolute difference and percentage of the lowest quartile). Results are broken down by deal age (in semesters) and overall ("All"). Definitions of all the variables are provided in Appendix Table A1.

Panel A: Lasso Regression

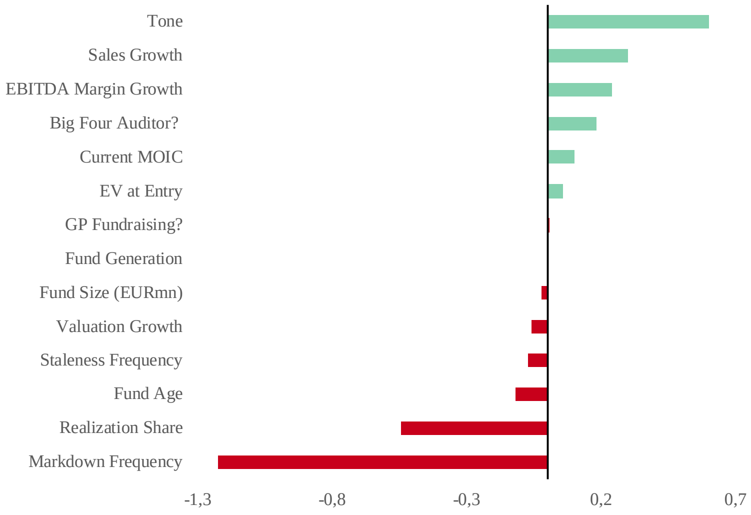
		Predicted MOIC uplift Quartiles:				
	Total	Lowest	3rd	2nd	Highest	High – Low
All		0,15x	0,76x	1,14x	1,63x	1,49x
Deal Age (in Semesters):						
2	1,68x	0,04x	1,51x	1,13x	2,02x	1,98x
4	1,27x	-0,25x	0,50x	1,44x	1,63x	1,88x
6	1,01x	0,13x	0,66x	1,18x	1,46x	1,33x
8	0,64x	0,27x	0,73x	0,68x	0,81x	0,54x
10	0,49x	-0,05x	0,47x	0,98x	1,42x	1,47x

Panel B: Random Forest Regression

		Predicted MOIC uplift Quartiles:				
	Total	Lowest	3rd	2nd	Highest	High – Low
All		0,47x	0,53x	0,98x	1,69x	1,21x
Deal Age (in Semesters):						
2	1,68x	0,73x	0,53x	1,75x	1,98x	1,25x
4	1,27x	0,76x	0,59x	1,18x	1,71x	0,94x
6	1,01x	0,63x	0,82x	0,92x	1,51x	0,88x
8	0,64x	0,74x	0,23x	0,30x	2,56x	1,82x
10	0,49x	0,50x	0,31x	0,34x	1,60x	1,09x

Figure 1 Most relevant Deal Characteristics to predict Deal Performance

This figure illustrates the standardized coefficients of the most significant predictors of deal performance using Lasso Regression. The model is trained on deals exited before 2017 and applied to subsequent deals to predict whether the MOIC uplift will be above the median. Positive coefficients (in green) indicate variables that positively contribute to deal success, while negative coefficients (in red) indicate factors negatively associated with performance. Definitions of all the variables are provided in Appendix Table A1.



Appendix

Table A1 Variable definitions

Performance Measures	Definition
Interim MOIC	Ratio of all capital distributions plus the last reported Fair Market Value to the total amount of capital invested (excluding fees)
MOIC Uplift	Difference between the exit MOIC and interim MOIC
Staleness Frequency	Percentage of past periods without change in MOIC as in Eren et al. (2024)
Markdown Frequency	Percentage of past periods with MOIC markdown as in Eren et al. (2024)
Realization Value	Ratio of all capital distributions to the sum of capital distributions and the last reported Fair Market Value (excluding fees)
Qualitative Information	**Definition**
Report Tone	Average tone across sentences in the Company section update where each sentence is classified as negative (-1), neutral (0), or positive (1) using FinBERT developed by Huang, Wang, and Yang (2020), which is an NLP trained on corporate reports, earnings call transcripts, and analyst reports
Tone [FinRoBERTa]	Average tone across sentences in the Company section update where each sentence is classified as negative (-1), neutral (0), or positive (1) using FinRoBERTa, which is an NLP model pre-trained on a large corpus of financial documents, including financial statements, earnings announcements, earnings call transcripts, CSR reports, ESG news, and financial news
Tone [LM Dictionary]	Average tone across words in the Company section update where each word is classified as negative (-1) or positive (1) using the Loughran and McDonalds dictionary (2011)
Number of Sentences (ln)	Number of sentences in the Company update section
Financial Metrics	**Definition**
LN Sales Annual Growth	Delta in LN Sales divided by time passed (in years) as in Acharya et al. (2012)
EBITDA Margin Annual Growth	Delta in EBITDA margin divided by time passed (in years) as in Acharya et al. (2012)
Valuation Annual Growth	Delta in EBITDA multiple divided by time passed (in years) as in Acharya et al. (2012)
Leverage	Net Debt to Enterprise Value
LN EV at Entry	Natural log of the Enterprise Value at entry
Fund Characteristics	**Definition**
GP raising next fund?	Binary variable adopting a value of one if the manager is raising a follow-on fund, and zero otherwise
Big Four Auditor?	Binary variable adopting a value of one if the auditor is one of the “big four”, and zero otherwise
LN Fund Size (EURmn)	Natural log of the amount of capital a fund has under management (in millions of Euros)
Fund Generation	Sequence number of a fund for a certain investment strategy by a PE firm
Fund Age	Number of years passed since the first investment of the fund

Table A2 Exit Deal MOIC (Realized, partially realized, and unrealized deals)

This table presents regression results analyzing the determinants of Exit MOIC (Multiple of Invested Capital) at the deal level. The dependent variable in all models is Exit MOIC. Key explanatory variables include measures of Report Tone, interim MOIC, staleness and markdown frequency, deal-level financial metrics (e.g., sales growth, margin growth), and fund characteristics (e.g., fund size and age). The table includes fixed effects for semester, investment year, industry, and region as indicated. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)
			Exit MOIC		
Report Tone		0.584[a]	0.550[a]	0.515[a]	0.562[a]
		(0.033)	(0.035)	(0.035)	(0.035)
Interim MOIC	1.069[a]	1.039[a]	1.043[a]	1.029[a]	1.021[a]
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
LN Sales Growth			0.066	0.082	0.104[b]
			(0.051)	(0.051)	(0.051)
EBITDA Margin Growth			0.047[b]	0.046[b]	0.047[b]
			(0.021)	(0.020)	(0.020)
Valuation Growth			0.029[b]	0.018	0.016
			(0.014)	(0.014)	(0.014)
LN EV at Entry			0.005	0.023[a]	0.068[a]
			(0.007)	(0.007)	(0.009)
Realization Value			-0.192[a]	-0.217[a]	-0.179[a]
			(0.047)	(0.047)	(0.047)
GP Fundraising? [0/1]			-0.034	-0.042	-0.038
			(0.035)	(0.035)	(0.035)
Year-end Report? [0/1]			0.006	0.008	-0.023
			(0.025)	(0.024)	(0.025)
Big Four Auditor? [0/1]			0.148[a]	0.170[a]	0.174[a]
			(0.046)	(0.047)	(0.047)
LN Fund Size (EURmn)					-0.091[a]
					(0.014)
Fund Generation					-0.005
					(0.007)
Fund Age					-0.077[a]
					(0.008)
Constant	0.555[a]	0.463[a]	0.213	-0.111	1.388[a]
	(0.019)	(0.020)	(0.136)	(0.142)	(0.231)
Observations	20,343	20,343	17,541	17,541	17,541
Semester FE	YES	YES	YES	YES	YES
Investment Year FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Region FE	NO	NO	NO	YES	YES
Adj. R-squared	0.353	0.363	0.394	0.406	0.412

Table A3: Drivers of Exit MOIC by Investment Age

This table presents regression results analyzing the determinants of Exit MOIC (Multiple of Invested Capital) across five years following deal start. The analysis is clustered at the portfolio firm level, with separate regressions conducted for each year. Explanatory variables include Report Tone, Interim MOIC, measures of deal performance (e.g., Staleness and Markdown Frequency), deal-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth), and fund-level factors (e.g., Fundraising, Big Four Auditor, Fund Size, Fund Generation, and Fund Age). Fixed effects for semester, industry, and region are included. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)
	Exit MOIC				
	Year 1	Year 2	Year 3	Year 4	Year 5
Report Tone	0.964[a]	0.596[a]	0.674[a]	0.475[a]	0.479[a]
	(0.108)	(0.097)	(0.091)	(0.090)	(0.086)
Interim MOIC	1.077[a]	1.140[a]	1.063[a]	1.025[a]	1.018[a]
	(0.068)	(0.040)	(0.031)	(0.027)	(0.024)
LN Sales Growth	0.018	0.087	0.072	0.302	0.233
	(0.084)	(0.148)	(0.164)	(0.196)	(0.236)
EBITDA Margin Growth	0.281	0.016	0.342[a]	0.097	0.270
	(0.180)	(0.026)	(0.098)	(0.147)	(0.439)
Valuation Growth	0.001	-0.006	-0.013	0.020	0.057
	(0.033)	(0.037)	(0.038)	(0.040)	(0.041)
LN EV at Entry	0.111[a]	0.090[a]	0.080[a]	0.063[a]	0.027
	(0.027)	(0.025)	(0.024)	(0.024)	(0.023)
Realization Value	-0.333	-0.627[a]	-0.373[a]	-0.217[c]	-0.219[b]
	(0.292)	(0.169)	(0.131)	(0.113)	(0.099)
GP Fundraising? [0/1]	0.279[a]	0.010	-0.187[b]	-0.246[a]	-0.126
	(0.094)	(0.081)	(0.082)	(0.090)	(0.097)
Year-end Report? [0/1]	-0.055	-0.076	0.001	-0.053	-0.028
	(0.072)	(0.067)	(0.064)	(0.062)	(0.060)
Big Four Auditor? [0/1]	0.074	0.258[c]	0.226[c]	0.181	0.179
	(0.151)	(0.139)	(0.127)	(0.114)	(0.110)
LN Fund Size (EURmn)	-0.105[a]	-0.100[a]	-0.114[a]	-0.089[b]	-0.100[a]
	(0.040)	(0.037)	(0.036)	(0.035)	(0.035)
Fund Generation	-0.030	0.005	-0.003	-0.009	0.007
	(0.020)	(0.018)	(0.018)	(0.017)	(0.016)
Fund Age	-0.136[a]	-0.095[a]	-0.099[a]	-0.075[a]	-0.043[c]
	(0.025)	(0.023)	(0.022)	(0.022)	(0.022)
Constant	1.328[c]	1.137[c]	1.645[a]	1.359[b]	1.872[a]
	(0.692)	(0.630)	(0.603)	(0.587)	(0.566)
Observations	3,228	3,089	2,824	2,408	1,948
Adj. R-squared	0.174	0.312	0.403	0.488	0.584

Table A4 Alternative Measures of Tone and Exit MOIC

This table presents regression results analyzing the determinants of Exit MOIC (Multiple of Invested Capital) using alternative qualitative measures. The models evaluate "All Deals" and "Realized Deals" using three deal tone measures: Abnormal FinBERT tone, FinRoBERTa tone, and Dictionary-based tone (Loughran-McDonald 2011). Abnormal FinBERT tone is the residual of regressing FinBERT on performance metrics (e.g., Interim MOIC, Staleness Frequency, Markdown Frequency), deal-level financial metrics (e.g., Sales Growth, EBITDA Margin Growth), fund-level controls (e.g., Fund Size, Fund Age), and fixed effects. Fixed effects for semester, industry, and region are included. Standard errors are reported in parentheses. [a], [b], and [c] denote statistical significance at the 1%, 5%, and 10% levels, respectively. Definitions of all the variables are provided in Appendix Table A1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Exit MOIC – Interim MOIC					
	All Deals			Fully realized Deals		
	Abnormal FinBERT	FinRoBERTa	Dictionary LM 2011	Abnormal FinBERT	FinRoBERTa	Dictionary LM 2011
Report Tone	0.526[a]	0.517[a]	7.146[a]	0.603[a]	0.572[a]	7.978[a]
	(0.038)	(0.037)	(0.619)	(0.044)	(0.044)	(0.721)
Interim MOIC	0.061[a]	0.038[a]	0.046[a]	0.075[a]	0.048[a]	0.056[a]
	(0.012)	(0.012)	(0.013)	(0.014)	(0.015)	(0.015)
LN Sales Growth	0.137[b]	0.098[c]	0.118[b]	0.187[a]	0.147[b]	0.174[a]
	(0.053)	(0.053)	(0.055)	(0.063)	(0.063)	(0.066)
EBITDA Margin Growth	0.046[b]	0.047[b]	0.044[b]	0.037[c]	0.037[c]	0.034
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Valuation Growth	0.020	0.018	0.014	0.029	0.028	0.018
	(0.015)	(0.015)	(0.016)	(0.018)	(0.018)	(0.019)
LN EV at Entry	0.067[a]	0.066[a]	0.070[a]	0.071[a]	0.069[a]	0.071[a]
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Realization Value	-0.026	0.045	0.050	-0.089	-0.009	-0.012
	(0.063)	(0.063)	(0.065)	(0.072)	(0.072)	(0.074)
GP Fundraising? [0/1]	-0.037	-0.039	-0.020	-0.036	-0.038	-0.034
	(0.037)	(0.037)	(0.038)	(0.042)	(0.042)	(0.043)
Year-end Report? [0/1]	-0.015	-0.019	-0.020	0.003	-0.003	-0.002
	(0.026)	(0.026)	(0.027)	(0.030)	(0.030)	(0.031)
Big Four Auditor? [0/1]	0.174[a]	0.193[a]	0.204[a]	0.155[b]	0.182[a]	0.179[a]
	(0.049)	(0.049)	(0.051)	(0.063)	(0.063)	(0.064)
LN Fund Size (EURmn)	-0.071[a]	-0.090[a]	-0.086[a]	-0.087[a]	-0.107[a]	-0.098[a]
	(0.015)	(0.015)	(0.015)	(0.017)	(0.017)	(0.017)
Fund Generation	-0.001	-0.004	-0.000	0.004	0.000	0.002
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)
Fund Age	-0.080[a]	-0.082[a]	-0.079[a]	-0.088[a]	-0.090[a]	-0.086[a]
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Constant	1.056[a]	1.349[a]	1.278[a]	1.417[a]	1.719[a]	1.596[a]
	(0.244)	(0.245)	(0.252)	(0.274)	(0.276)	(0.283)
Observations	16,472	16,472	15,585	12,998	12,998	12,320
Adj. R-squared	0.0832	0.0830	0.0798	0.0970	0.0960	0.0899