Moving Targets*

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We find that managers strategically shift targets in their communications with investors and markets. Using the complete history of the earnings conference call transcripts by U.S. corporations from 2006 – 2020, we employ natural language processing techniques to analyze the full text of these conference calls. Our approach leverages advanced natural language processing (NLP) techniques, specifically utilizing an English transformer pipeline that incorporates several integrated components: the RoBERTa transformer model, a part-of-speech tagger, a syntactic parser, an attribute ruler, a lemmatizer, and a named entity recognizer (NER). Managers choose and re-choose performance metrics (targets) to ensure they clear their endogenously chosen hurdle. For instance, if they have exceeded an endogenously set performance metric X for N periods, and then have private information they will fall short in period (N+1), they attempt to shift to metric Y. When managers change the target, this predicts significant negative returns and realizations for the firm. In particular, in the quarter following a moved target, firms underperform by up to 99 basis points per month (t-stat = 4.38) in value-weighted monthly abnormal return (alpha). Moreover, we find that the effects are significantly stronger with more complex targets, non-financial targets, and the most persistent targets. Further, when attention is paid to the dropped targets in real-time, and CEOs are pressed to address the moving target, the return effects are attenuated.

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Targets are used ubiquitously throughout society. Sales targets, growth targets, exercise targets, etc., are all examples of how targets are used throughout economies and agents' lives. Targets are made in order to have a verifiable ex-ante metric that can be easily compared against ex-post. Targets can be fixed (e.g., sales revenues over 100M) or relative and floating (e.g., above the 75^{th} percentile in a firm's industry). When a firm has an externally imposed target, there is no scope for strategic behavior on the target itself. Relatively less attention has been paid to firms' abilities to move endogenously chosen targets, and to how broader market participants interpret these moving targets.

In this paper, we use the laboratory of firm earnings conference calls to examine this behavior by firms and reactions by market participants. Using the universe of conference calls made by firms from 2006-2020, we examine how firms strategically set, and then move, the targets that they use to measure and express firm growth. We show that firms consistently exploit this in the universe of publicly traded firms. We show that when firms "move" targets, it is largely because they can no longer attain the same level (or growth rate) around the given target. On average, this predicts negative realizations for the firm in terms of returns and real outcomes.

We find that managers strategically shift targets in their communications with investors and markets. We employ natural language processing techniques to analyze conference calls and find that managers choose and re-choose targets to ensure they clear their endogenously chosen hurdle. Managers changing the target predict significant negative returns and realizations for the firm in question. In the quarter following a moving target, firms underperform by an average of 78 basis points per month (t-stat = 4.38) in value-weighted monthly abnormal return (alpha, or over 9% per year in abnormal return). These returns continue to accrue out to 18 months and do not reverse, implying that far from overreaction, these changes imply true, fundamental information for firms that only gets gradually incorporated into asset prices in the months after the reporting change. Even though not mandated, a large number of publicly traded firms have earnings conference calls, the sample over which we show these abnormal returns is truly the universe of firms (not a small, illiquid, or otherwise selected subset).

We show that these findings cannot be explained by traditional risk factors, well-known predictors of future returns, unexpected earnings surprises, or news releases that coincide with the timing of these firm disclosures. Moreover, we find an economically and statistically zero announcement day return in the full sample. This contrasts with a gradual information diffusion type explanation that is consistent with the empirical pattern of many other regularities (e.g., post-earnings announcement drift, momentum, etc.), in which there is an immediate large response followed by a much more modest – but persistent – drift in the same direction. Instead, the pattern we document is more consistent with investors simply failing to account for – or be attentive – the systematic and rich information contained in simple modification of the target sets. Their stock prices exhibit little to no reaction at the time of dropping previously discussed targets by the firm, even though there is a robust and systematic relationship (whereby changes predict future negative returns and negative real operational realizations) – with the information only being impounded into the price in the future.

Next, we explore the mechanism at work behind these return results. We show that these returns are larger when firms use a larger and more complex set of targets. Moreover, the returns are also larger for non-financial targets vs. financial targets (e.g., subscribers, iPhone vs. revenue, or sales growth). Lastly, the results become even stronger the longer and more engrained the target is at the firm. When managers change 'persistent' targets, returns increase to 99 basis points per month (t-stat = 4.40) in value-weighted monthly abnormal returns, so nearly 12% per year. Investors should pay close attention to the metrics upon which firms choose to focus, and the subtle changes to those metrics that firms make over time, as moving targets contain important information for future firm value and realizations.

We then turn to measures of real activity and show that moving targets predict future earnings, profitability, future news announcements, and the future value of those targets. Moreover, much like return realizations, these appear to be largely unanticipated, as the real operational changes are not taken into account by analysts covering the firm – resulting in the moving targets significantly predicting future negative earnings surprises and negative cumulative abnormal returns (CARs) around these events.

Lastly, we do several robustness checks across firm size, time, industry, firm events, etc. The effect that we document is not driven by any of these factors. It is not something about special firm events or certain industries, types, or characteristics of firms. In addition, this does not appear to be a function of transaction costs or limits to arbitrage. The return results that we document have the following characteristics: they accrue over *months* following the earnings conference call (so no high-frequency trading is needed); the portfolios have very modest turnover (around the infrequent reporting dates); the effects show up in value-weighted returns across the universe of all publicly traded firms (and so are not concentrated in small firms); the average targets movers firm (to be shorted) is larger than the average length, and the average changer firm has relatively modest shorting fees – again actually less costly to short than the average stock in the long portfolio.

Stepping back, these results in some manner require a differential inattention of investors with respect to non-financial targets compared with financial targets. We find that when analysts who attend those conference calls prompt dynamic highlighting of a dropped target by a CEO, and when the CEO is forced to address those missing targets, the firm attenuates this moving target effect considerably.

Summing up, investors should pay close attention to the metrics upon which firms choose to focus, and the subtle changes to those metrics that firms make over time, as moving targets contain important information for future firm value and realizations. The remainder of the paper is organized as follows. Section I provides a brief background and literature review. Section II describes the data we use and explores the construction of firms' target sets and the dynamics of those target sets. Section III examines the impact of these choices, and Section IV explores the mechanism driving our results in more detail. Section V concludes.

I. Background and Related Literature

Our paper contributes to several growing literature, including (but not limited to): a) the broad topic of underreaction in stock prices and the impact of investor inattention; b) the use of textual analysis in finance and accounting; and c) the information content of firms' disclosure choices.

The magnitude and nature of our return predictability results add new evidence and much-needed granularity to the existing stock price underreaction and inattention literature. As described in Tetlock (2014)'s review article, several papers document that underreaction is strongest when investors fail to pay attention to informative content. See, for example, Tetlock (2011), who constructs measures of "stale" news stories and demonstrates that investors overreact to stale information (and correspondingly, underreact to novel information). In addition, Da, Engelberg, and Gao (2011, JF) use Google search activity to pinpoint retail investor attention, while Ben-Raphael, Da, and Israelson

(2017) measure institutional attention using Bloomberg search activity; the latter shows that stock price drift is most pronounced for stocks with the least amount of institutional attention. Another novel measure of attention is employed by Engelberg, Sasseville, and Williams (2012), who show that spikes in TV ratings (presumably driven by retail investors) during the Jim Cramer "Mad Money" show are linked to an overreaction in stock prices for the companies recommended during the show. By contrast, what we document in this paper is an acute form of investor inattention that impacts a large cross-section of firms, is centered on the most important corporate events that firms make and leads to large return predictability.

Furthermore, we use novel data and features of the earnings conference call to demonstrate that variation in attention to various targets produces variation in these return predictability patterns. And finally, we dig into the nature of this inattention and show that investors have an easier time digesting financial targets, but less so for non-financial targets. So, it is not merely the difference between quantitative and qualitative information that matters for investors (as in Engelberg (2008)), but also how that qualitative information is constructed and presented. In these ways, our paper helps to micro-found some of the more general evidence on inattention and underreaction in stock prices by clarifying exactly what it is that investors fail to recognize.

Our paper also contributes to the large and fast-growing field of textual analysis and natural language processing in finance and accounting. As a result of increased computing power and advances in the field of natural language processing, many recent papers have tried to employ automated forms of textual analysis to answer important questions in finance and accounting; Loughran and McDonald (2016) provide a helpful survey of some of these papers. Most relevant to our study are the articles that analyze the link between textual information in firm disclosures (such as the 10-Ks and 10-Qs that feature in our analysis) and firm behavior and performance. For example, Li (2008) employs a form of textual analysis and finds that the annual reports of firms with lower earnings (as well as those with positive but less persistent earnings) are harder to interpret. Li (2010a) also finds that firms' tone in forward-looking statements in the MD&A section can be used to predict future earnings surprises. Meanwhile, Nelson and Pritchard (2007) explore the use of cautionary language designed to invoke the safe harbor provision under the Private Securities Litigation Reform Act of 1995 and find that firms that are subject to greater litigation risk change their cautionary language to a larger degree relative to the previous year; but after a decrease in litigation risk, they fail to remove the previous cautionary language. In addition, Feldman et al. (2010) find that a positive tone in the MD&A section is associated with modestly higher contemporaneous and future returns and that an increasingly negative tone is associated with lower contemporaneous returns.

Finally, our work contributes to the ongoing literature on how firms shape their information environments, the diverse channels they use for market communication, and the consequences of these choices for investors, customers, regulators, and other key audiences. Empirical evidence suggests that managers engage in strategic information disclosure timing. Hirshleifer et al. (2009), DellaVigna and Pollet (2009), and Neissner (2013) document a tendency for managers to release positive news during periods of perceived low investor focus. This phenomenon is further corroborated by research on negative news timing, as evidenced by the work of Kothari et al. (2009), Bergman and Roychowdhury (2008), and Westphal and Deephouse (2011).

Given our use of quarterly earnings conference calls as a research lens, our study aligns with the broader literature investigating the interplay between companies and analysts, as well as research on the information revealed through earnings announcements and dedicated conference calls. Extensive research has linked conference call communication with various outcomes, including information content (Hollander et al., 2010; Matsumoto et al., 2011), information asymmetry (Chen et al., 2014), future performance (Mayew & Venkatachalam, 2012), and financial misconduct (Larcker & Zakolyukina, 2011; Hobson et al., 2012). Studies have also examined how language choices (Zhou, 2014) and analyst access to management (Chen & Matsumoto, 2006) can influence outcomes.

II. Data and Summary Statistics

We draw from a variety of data sources to construct the sample we use in this paper. We obtain conference call transcripts from S&P Capital IQ and Refinitiv StreetEvents. Both data vendor collects transcripts that are verbatim representations of corporate and institutional events. There are unique advantages for each data vendor. S&P Capital IQ has a clear identifier for different component types of each conference call: (1) the initial presentation by management at the beginning of each conference call (Component Type ID = 2, Presenter Speech), (2) questions asked by analysts (Component Type ID = 3, Question), and (3) the answers and response for each question (Component Type ID = 4, Answer). Another big advantage of the S&P Capital IQ conference call is a unique identifier for each analyst participating in different conference calls across different companies (Transcript Person ID).

Even though S&P Capital IQ goes back to 1990, the coverage before 2009 is sparse. Refinitiv StreetEvents covers approximately 7,200 global companies and has much better coverage for conference calls than before 2009. We use NLP techniques to extract and create the same component identifier for Refinitiv StreetEvents conference calls similar to that of S&P Capital IQ to extend the data coverage for our final sample (Component Type ID: Speech, Questions, and Answers). Our sample contains.

We obtain monthly stock returns from the Center for Research in Security Prices (CRSP) and firms' book value of equity and earnings per share from Compustat. We obtain analyst data from the Institutional Brokers Estimate System (IBES). Our final dataset for conference call transcripts covers 4848 firms and spans from 2006 – 2020.

We use spaCy, a free, open-source library for advanced Natural Language Processing (NLP) in Python to analyze firms' quarterly earning call transcripts. We utilize spaCy's pre-trained pipelines that consist of multiple components that use a statistical model trained on labeled data text data. More specifically, we use en_core_web_trf, which is an English pipeline trained on written web text (blogs, news, comments), that includes vocabulary, syntax, and entities. spaCy's trained pipelines include a tagger, a lemmatizer, a parser, and an entity recognizer.

We identify *targets* using two methods. We use spaCy's Named Entity Recognition to search for named entities that are **Products**, **Money,** or **Percent.** All noun-chunks that are **Product** entity are recorded as a target. For each named entity in a sentence that is either a *Money* entity or a *Percentage* entity**,** we use spaCy's Part-of-Speech method to identify the nouns and noun chunks that those entities are related to.

Figure 1A shows an excerpt of Apple's fourth quarter Conference Call on October 9th, 2019. We first identify all named entities that are **Product** (highlighted in yellow: Macs, Macbooks, Snow Leopard), **Money** (highlighted in green: $9.87 billion, $2.19 billion, $1.82 billion, etc.), and **Percent** (highlighted in purple: 25%, over 22%, 2%, etc.). "Mac", which is a company's product, is classified and recorded as a target. For **Money** and **Percent** entities, we further used Part-of-Speech to extract the subject the percent entity is referring to.

Figure 1B shows an example to demonstrate how we use Part-Of-Speech to identify a target. Let's consider another sentence from the same conference call:

"Net income was $1.67 billion, which translated to earnings per share of $1.82."

The phrase "$1.67 billion", highlighted in green, is identified as a "**Money"** entity. We then use the Part-of-Speech model to extract the target this "**Money"** entity is referring to. The "**Money"** entity noun-chunk "$1.67 billion" is an attribute of the verb **was** (AUX). The noun-subject (nsubj) that the auxiliary verb "**was"** (AUX) is pointing to is "**Net income"**, which we then record as a target. Figure 1C shows another example where we identify targets from "**Percentage"** named entities. Consider another example from the previous excerpt:

"We were very pleased with the 12% year-over-year increase in Mac sales to US education institutions"

The phrase "12%", highlighted in purple, is identified as a "**Percent"** entity. The "**Percent"** entity "12%" is a modifier-of-nominal (nmod) of the noun "**increase"** (NOUN). From the noun "**increase"**, we then identify the prepositional modifier (prep), "**in"**, and subsequently, the object-of-preposition (pobj), "**Mac sales**", which we then record as a target.

[Figure 1 HERE]

Figure 2 shows the target sets collected from the presentation sections of Apple Inc.'s Q4 Earnings conference calls from 2006 to 2015. The font size of each target represents the frequency of that target in an earnings conference call. Targets include financial targets, such as revenue, sale, net income, OI&E, cash rate, tax rate, etc., and non-financial targets, such as Mac, iPhone, iPad, etc. Target sets change over time and there is a great variation in the intensity of targets.

For example, the target “iPod” was frequently mentioned in 2006, 2007, and 2008, but started to diminish since then, which coincides with the decline in the sales number and importance of the iPod to Apple since then. “iPhone”, which is absent in 2006, started to become a frequent and dominant target since the introduction of the first iPhone in June 2007. Similarly, the target “iPad” started to become a frequent target since its introduction in 2010. Interestingly, the target “iPad” became less significant since 2014, which also coincides with its peak sales number in the fourth quarter of 2014. Apple Pay was introduced in October 2014, which is also reflected in the target “Apple Pay” has been discussed regularly since then. On financial targets, “tax rate” was regularly mentioned since 2009, with the intensity increase over the period 2009-2013, which coincides with the dramatic drops of Apple’s effective tax rate over the same period.[12]

[Figure 2 HERE]

Table 1, Panel A presents summary statistics from our final dataset, which consists of all earnings conference call transcripts from 2006 to 2020. *Word Count Transcript* is the number of words in the entire transcript. *Word Count Presentation*, *Word Count Question*, and *Word Count Answer* are the number of words in each of the components of an earnings conference call. On average, a conference call contains 7115 words, the presentation component contains 2954 words, and the answer component contains 2874 words on average. We measure the quarter-on-quarter Moving Targets as

[1] https://americansfortaxfairness.org/files/OPENING-STMT-LEVIN-Carl-Offshore-Profit-Shifting-Apple-5-21-13.pdf
[2] https://www.forbes.com/sites/timworstall/2012/04/18/apples-9-8-tax-rate-entirely-mind-gargling-nonsense/?sh=27733e25732c

follows:

$$Moving\ Targets_t = \frac{\sum\ (Missing\ Targets_t\ |\ Targets_{t-4})}{\sum\ Targets_{t-4}}$$

Panel B of Table I presents summary statistics of the number of targets and the main variable of interest, Moving Targets, which range from 0 to 1. An average earnings conference call has 126 targets. Higher values of *Moving Targets* indicate a higher degree of firms dropping their targets this quarter.

[Table I HERE]

III. The Implication of Firms' Moving Targets

In this section, we examine the implications of firms' decisions to drop a target. In particular, we explore the nature of these changes and their implications for firms' future actions and outcomes.

We begin by analyzing the future stock returns associated with firms that drop many of their targets, versus those that do not. First, we compute standard calendar-time portfolios, and then we control for additional determinants of returns by employing Fama-MacBeth monthly cross-sectional regressions.

A. Calendar-Time Portfolio Returns

We compute quintiles each month based on the prior month's distribution of Moving Targets across all stocks. For firms with a fiscal year-end in December, we use the following earnings conference call: for calendar quarter Q1, we use the release of a firm's Q1 earnings conference call, which generally occurs in April or May; for calendar quarter Q2, we use another release of a firm's earnings conference call, which generally occurs in July or August; for calendar quarter Q3, we use another release of a firm's earnings conference call, which generally occurs in October or November; and finally for the year-end results we use the end of the year earnings conference call, which typically occurs in February of March. Moving Targets are computed relative to the prior year earnings conference call that lines up in calendar time with the report in question (such that 2010 Q1 is compared with 2009 Q1, for example). Stocks enter the portfolio in the month after the public release of one of their earnings conference calls, which induces a lag in our portfolio construction. Note that in all our tests, firms are held in the portfolio for 3 months. Portfolios are rebalanced monthly, and the average monthly returns are reported in Table II.

[Table II HERE]

Panel A of Table II presents equal-weighted calendar-time portfolio returns. Quintile 1 (Q1) refers to firms that have the least similarity between their document this year and the one last year; hence this portfolio consists of the "big target movers." Quintile 5 (Q5) refers to firms that have the most similarity in their documents across years, and hence this portfolio represents the "little to no target moved." Q5-Q1 represents the long-short (L/S) portfolio that goes long Q5 and short Q1 each month.

Panel A shows that this L/S portfolio earns a large and significant abnormal return, ranging in magnitude between 16-21 basis points per month. This result is unaffected by controlling for the 3

Fama-French factors (market, size, and value), or for two additional momentum and liquidity factors. This suggests that the return spreads we see between these portfolios are not driven by systematic loadings on commonly known risk factors. This finding indicates that firms that drop a significant number of their targets in a given year experience lower future returns. Later in the paper, we explore the possible mechanisms behind this return result.

Panel B of Table II then presents value-weight portfolio returns, computed as in Panel A except that each stock in the portfolio is weighted by its (lagged) market capitalization. Panel B shows that the value-weight portfolio returns are similar but somewhat larger in magnitude to the equal-weight results, with the value-weight L/S portfolio earning up to 55 basis points per month (t=3.89), depending on the similarity measure employed.

Decomposing the L/S spread into its components, Panel B of Table II also shows that a similar portion of the L/S spread comes from both the short and long sides of the portfolio, although that is not true across every specification. We explore the evolution of both the long and short legs of this portfolio using event-time returns in Figure 3. As seen from the event-time returns in Figure 3, any positive alpha on the Q1 long side (the "little to no movers") and the negative alpha persists and increases up to 12 months out – never reversing. Taken as a whole, Figure 7 suggests that the information contained in a firm's decision to significantly change its reporting practices has a long-lasting impact on the firm value that does not accrue upon release of reports, but instead only gradually through price revelation over time.

B. Characteristics of Quintile Portfolios

The finding that much of the return spread documented in Table II and Figure 7 comes from both the long and the short sides begs the question of the composition and characteristics of both sides of this L/S portfolio. For example, it could be the case that the short side simply contains a set of smaller firms that are difficult (and expensive) to short. Or perhaps, there is no significant turnover of small or illiquid stocks to trade. Both of these might make the returns we document fall within simple limits of arbitrage. Table III presents the average size, turnover, and moving targets (as defined in Table I) for all five quintile portfolios. As Table III shows, there is little evidence that the short or long side contains an unusual set of firms on average; if anything, the firms in Q1 appear to be slightly larger and have lower average turnover. Moreover, given that turnover is so modest, that VW returns are a bit larger than EW, that our sample is the entire universe of publicly traded firms resulting in large, diversified portfolios for each quintile, and that returns only accrue slowly over the following 12 months, we do not believe limits to arbitrage are a significant contributor to the return regularities we see.

[Table III HERE]

C. Fama-MacBeth Regression

We next run monthly Fama-MacBeth cross-sectional regressions of future individual firm-level stock returns on a host of known return predictors, plus our 4 similarity measures. As Table IV shows, each similarity measure is a positive and significant predictor of future stock returns, implying that firms who make large changes to their reports experience lower future returns. This result holds when we include a variety of additional return predictors as well, including the following: last month's (or last quarter's) standardized unexpected earnings surprise (*SUE*); *Size,* the log market value of equity; *log(BM)*, the log book value of equity over the market value of equity; *Ret(-1,0),* the previous month's return; and *Ret(-12, -2),* the cumulative stock return from month *t*-12 to month *t*-2. SUE is computed as actual earnings per share minus average analyst forecast earnings per share, divided by the standard deviation of the forecasts.

[Table IV HERE]

In terms of magnitude, the coefficient on *Moving Targets* in column 3 (=0.0059, t = 3.2397), for example, implies that for a one-standard-deviation decline in a stock's document similarity across years, returns are 12 basis points lower per month in the future.

IV. Mechanism

In this section, we explore the mechanism at work behind our key return results.

A. Complexity of Target Sets

We explore our mechanism in even greater depth by trying to isolate cases where we believe it's harder for investors to pay more attention to firms moving their targets, meaning that our return effects should be muted in such instances if we believe our return predictability results are primarily a result of investor inattention. To identify variations in investor attention, we separate firms with target sets that are more complex versus firms with less complex target set.

[Table V HERE]

Table V shows that this pattern exists in the data. The results are significantly larger for more complex target sets, measured using the number of targets that a firm regularly utilizes. Stronger return predictability is found when the target sets are more complex (=-0.0106, t-stat = 3.7212) and there is no significant return predictability when the target sets is simpler (=-0.0030, t-stat = -1.1713)

B. Persistence of Targets.

We define a target to be persistent if it was discussed consecutively in the previous three years.

$$Persistent\ Moving\ Targets_t = \frac{\sum\ (Missing\ Targets_t \mid Targets_{\{t-12,\ t-8,\ and\ t-4\}})}{\frac{1}{3}\sum Targets_{\{t-12,\ t-8,\ and\ t-4\}}}$$

[Table VI HERE]

Table VI shows that this pattern exists in the data. The results are significantly larger for more complex target sets, measured using the number of targets that a firm regularly utilizes. Stronger return predictability is found when the targets are more persistent (=-0.0149, t-stat = 4.4185) and there is no significant return predictability when the targets are less persistent (=-0.0009, t-stat = -0.2668). Consistent with the target – and moving of the target – is the important dynamic driving the results, we find that the results are significantly more concentrated (larger and more significant) for targets that are the most persistently utilized by firms and firm management.

C. Financial vs Non-Financial Targets

We hypothesize that non-financial targets are harder to evaluate compared to financial targets. Publicly traded firms are mandated to file financial reports and standardized financial targets, and hence these are harder for management to easier to be analyzed. Moreover, the returns are also larger for non-financial targets vs. financial targets (e.g., subscribers, iPhone vs. revenue, or sales growth).

[Table VII HERE]

Table VII shows that the results are weaker in point estimate for explicit financial targets (-0.0027, t-stat = -1.7431), and relatively stronger for more unique, firm specific targets (-0.0046, t-stat = 2.6671).

D. Analyst Interaction

We explore our mechanism in even greater depth by trying to isolate cases where we believe investors *are* paying more attention to firms moving their targets, meaning that our return effects should be muted in such instances if we believe our return predictability results are primarily a result of investor inattention. To identify variations in investor attention, we separate targets from three different components of the earnings conference call transcript: (a) the presentation, (b) analysts' questions, and (c) answers from the management to try to test the hypothesis that firms with more “attentive” investor bases see a more muted return predictability effect.

To test this hypothesis, we run Fama-MacBeth cross-sectional regressions for three different scenarios: (1) the targets are dropped in the presentation section. (2) The dropped targets are reintroduced if an analyst asks about them, and (3) the CEO answers the questions and mentioned the dropped target from the presentation. The idea behind this test is that if analysts inquire about a target that was not mentioned in the presentation, and moreover, if the CEO is forced to answer the questions about that target, analysts will pick up on the target changes driving our return results; as a result, we expect them to impound this information into prices more quickly, resulting in lower future return predictability.

[Table VIII HERE]

Table VIII shows that this pattern exists in the data. The strongest return predictability is found when targets are dropped during the presentation (=-0.0062, t-stat=3.3593). However, if analysts asked about those dropped targets, the return predictability is slightly weaker (=-0.0056, t-stat = 3.0003), and drops significantly to half the magnitude (=-0.0032, t-stat = 1.3367) and is no longer significant when the CEO is forced to answer and address those dropped targets. Analyst prompt dynamic highlighting of a dropped target by a CEO and firm attenuates this moving target effect considerably.

V. Conclusion

Targets are used ubiquitously throughout society. Sales targets, growth targets, exercise targets, etc., are all examples of common targets throughout economies, as well as in agents' lives. While many are externally imposed (and so less subject to manipulation), a large number are internally generated, and so more exposed to the potential of ex-post strategic manipulation. We focus in this paper on endogenously chosen targets made by firms, showing systematic evidence of firms moving these targets at times most strategically beneficial. In particular, across the universe of publicly traded firms, firms on average strategically move their targets in reporting performance to investors precisely when they can no longer reach the ex-ante benchmark targeted.

However, investors fail to realize or take into account the valuable information in these simple changes in targets. A portfolio that shorts target "mover" and buys target "non-movers" in annual and quarterly financial reports earns 30-99 basis points per month over the following year. The returns continue to accrue out to 12 months and do not reverse, implying that these return movements are not overreactions, but instead reflect true, fundamental changes to firms that only get gradually incorporated into asset prices over the 6-12 months after the reporting change. Importantly, these return patterns are found across the entire universe of publicly traded firms (as nearly all public companies hold pre-specified and regular quarterly earnings conference calls), exist in large firms, are present in inexpensive to short firms, and take place over months, and so are unlikely to be driven by a limit to arbitrage. Moreover, unlike other traditional drift regularities (e.g., return momentum, industry momentum, PEAD), these documented changes are not accompanied by any significant announcement returns, and so are inconsistent with a standard underreaction story (as there is no initial reaction). Instead, they are more consistent with a setting where investors ignore this rich information, which is only then impounded into prices with a significant delay.

The systematic patterns we document throughout the paper are consistent with a differential level of inattention of investors with respect to non-financial targets relative to numerical financial targets. Changes in targets that are more complex and persistent are especially informative for future returns. Changes in persistent targets, for instance, are associated with underperformance relative to non-changers of up to over 11% per year (t = 4.378).

Our evidence suggests that investors do not appear to be doing the same comparison of this year's non-financial targets to the last, leading to the rich information contained in these differences being largely missed by investors and the market. Indeed, when we measure investors' and analysts' propensity to inquire about this year's missing targets, we find that the returns are significantly attenuated.

Stepping back, given how ubiquitously targets are used throughout financial markets and communications (from firms, to policy makers, to Central Banks) – understanding this subtle ability to move targets, along with target-moving implications, can be first-order in understanding future likely dynamics. While technology and technological advancements in information collection and processing could aid in this, we show that far from needing complicated state-of-the-art solutions, simply collecting performance targets from year to year contain powerful information, which is seemingly being ignored by capital markets. This simple insight likely applies more broadly to other forms of transmitted firm information, as well. Documents and verbal communications, such as bond covenants, lease arrangements, securities offering documents, M&A prospectuses, interviews, investor presentations, and shareholder meetings may be rich places for researchers to explore further. More broadly, the implications of moving endogenously specified targets in the corporate setting provide a critical, yet understudied area, in both corporate finance and asset pricing.

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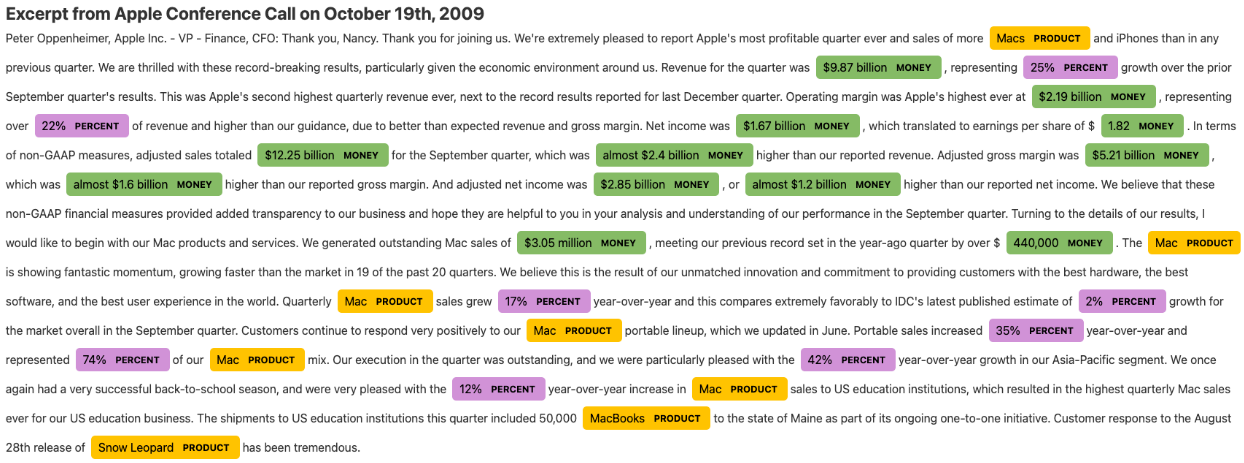
Figure 1: Sample Part of Speech to Identify Targets

Figure 1A



Excerpt from Apple Conference Call on October 19th, 2009

Peter Oppenheimer, Apple Inc. - VP - Finance, CFO: Thank you, Nancy. Thank you for joining us. We're extremely pleased to report Apple's most profitable quarter ever and sales of more Macs PRODUCT and iPhones than in any previous quarter. We are thrilled with these record-breaking results, particularly given the economic environment around us. Revenue for the quarter was $9.87 billion MONEY , representing 25% PERCENT growth over the prior September quarter's results. This was Apple's second highest quarterly revenue ever, next to the record results reported for last December quarter. Operating margin was Apple's highest ever at $2.19 billion MONEY , representing over 22% PERCENT of revenue and higher than our guidance, due to better than expected revenue and gross margin. Net income was $1.67 billion MONEY , which translated to earnings per share of $ 1.82 MONEY . In terms of non-GAAP measures, adjusted sales totaled $12.25 billion MONEY for the September quarter, which was almost $2.4 billion MONEY higher than our reported revenue. Adjusted gross margin was $5.21 billion MONEY , which was almost $1.6 billion MONEY higher than our reported gross margin. And adjusted net income was $2.85 billion MONEY , or almost $1.2 billion MONEY higher than our reported net income. We believe that these non-GAAP financial measures provided added transparency to our business and hope they are helpful to you in your analysis and understanding of our performance in the September quarter. Turning to the details of our results, I would like to begin with our Mac products and services. We generated outstanding Mac sales of $3.05 million MONEY , meeting our previous record set in the year-ago quarter by over $ 440,000 MONEY . The Mac PRODUCT is showing fantastic momentum, growing faster than the market in 19 of the past 20 quarters. We believe this is the result of our unmatched innovation and commitment to providing customers with the best hardware, the best software, and the best user experience in the world. Quarterly Mac PRODUCT sales grew 17% PERCENT year-over-year and this compares extremely favorably to IDC's latest published estimate of 2% PERCENT growth for the market overall in the September quarter. Customers continue to respond very positively to our Mac PRODUCT portable lineup, which we updated in June. Portable sales increased 35% PERCENT year-over-year and represented 74% PERCENT of our Mac PRODUCT mix. Our execution in the quarter was outstanding, and we were particularly pleased with the 42% PERCENT year-over-year growth in our Asia-Pacific segment. We once again had a very successful back-to-school season, and were very pleased with the 12% PERCENT year-over-year increase in Mac PRODUCT sales to US education institutions, which resulted in the highest quarterly Mac sales ever for our US education business. The shipments to US education institutions this quarter included 50,000 MacBooks PRODUCT to the state of Maine as part of its ongoing one-to-one initiative. Customer response to the August 28th release of Snow Leopard PRODUCT has been tremendous.

Figure 1B

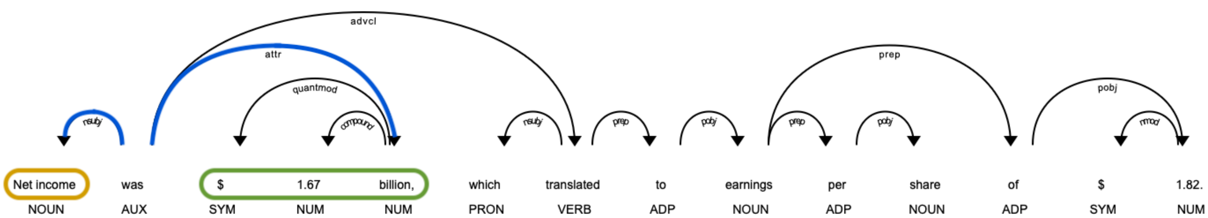


Figure 1C

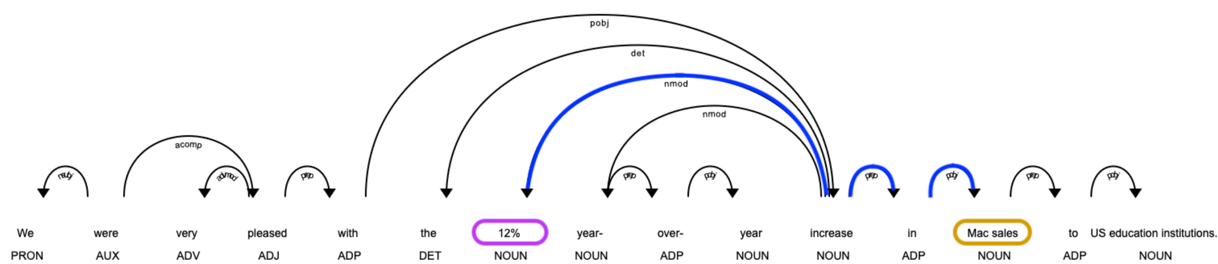


Figure 2: Sample Targets from Apple's Q4 Earnings Conference Calls

Figure 3: Event Time Returns

This figure plots the average cumulative abnormal return for the top (highest Moving Targets) and bottom (lowest Moving Targets) quintile portfolios. We compute quintiles based on the prior year's distribution of Moving Targets measures across all stocks. Abnormal return is return adjusted for market return. Events are dates of Earnings conference calls.

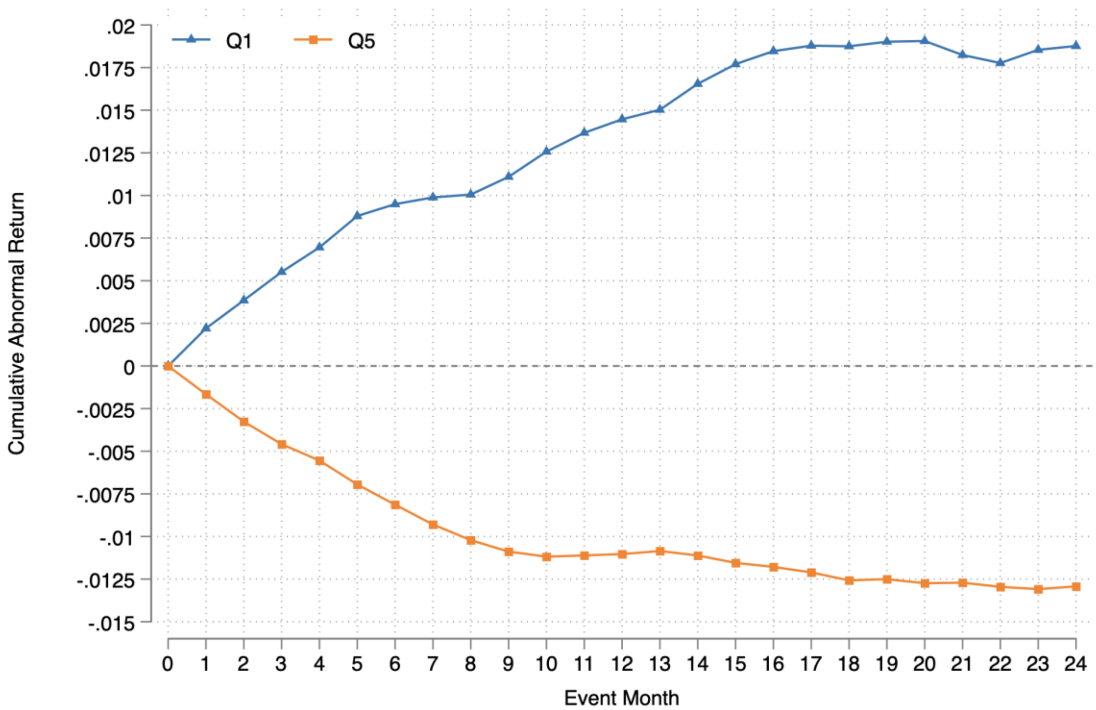


Table I: Summary Statistics

Panel A of this table reports the summary statistics of earnings conference calls from 2006 to 2020. *Panel B* reports the summary statistics of the main variable *Moving Targets*. *Word Count Transcript* is the number of words in the entire transcript. *Word Count Presentation*, *Word Count Question*, and *Word Count Answer* are the number of words in each of the components of an earnings conference call: Presentation, Question, and Answer. *Number of Targets* is the number of identified targets in each earnings conference call.

Panel A: Summary Statistics of Earnings Calls

	Count	Mean	SD	1%tile	99%tile
Word Count Transcript	143,153	7114.79	2634.002	1958	13889
Word Count Presentation	143,153	2954.491	1255.378	778	6593
Word Count Question	143,153	1135.295	587.9274	114	2772
Word Count Answer	143,153	2874.198	1536.23	127	7008

Panel B: Summary Statistics of Moving Targets

	Count	Mean	SD	1%tile	99%tile
Number of Targets	143153	126.9272	57.28876	28	300
Moving Targets	143153	.5572682	.1149202	.2758621	.8409091

Table II: Main Results – Calendar Time Portfolio Returns

This Table reports the calendar-time portfolio returns. We compute quintile/decile portfolios based on the prior year's distribution of *Moving Targets* across all stocks. Stocks then enter the quintile/decile portfolios in the month after each earnings conference call. Stocks are held in each quintile/decile portfolio until the next earnings conference call. We report Excess Returns (return minus risk-free rate), Fama-French 3-factor Alphas (market, size, and value), and 5-factor Alphas (market, size, value, momentum, and liquidity). *Panel A* reports equal-weight quintile portfolio returns, *Panel B* reports value-weight quintile portfolio returns, *Panel C* reports equal-weight decile portfolio returns, and *Panel D* reports value-weight decile portfolio returns. *t*-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A: Equally Weighted Quintile

	Moving Targets					
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Excess	0.0083*	0.0081*	0.0083*	0.0082*	0.0067	-0.0016**
Return	(1.9241)	(1.8067)	(1.8817)	(1.7944)	(1.4621)	(-2.2081)
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
3-Factor	-0.0000	-0.0004	-0.0001	-0.0006	-0.0021**	-0.0021***
Alpha	(-0.0341)	(-0.5567)	(-0.1051)	(-0.6895)	(-2.3137)	(-2.8669)
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
5-Factor	0.0002	-0.0001	0.0002	-0.0003	-0.0019**	-0.0021***
Alpha	(0.4232)	(-0.1847)	(0.2910)	(-0.4777)	(-2.3335)	(-2.8418)

Panel B: Value Weighted Quintile

	Moving Targets					
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
Excess	0.0109***	0.0081**	0.0077**	0.0076**	0.0061*	-0.0048***
Return	(3.0305)	(2.2999)	(2.1455)	(2.0781)	(1.6921)	(-3.5313)
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
3-Factor	0.0024**	0.0001	-0.0007	-0.0011	-0.0025***	-0.0050***
Alpha	(2.4089)	(0.1076)	(-1.0708)	(-1.3067)	(-3.1207)	(-3.5020)
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
5-Factor	0.0028***	0.0000	-0.0004	-0.0006	-0.0027***	-0.0055***
Alpha	(2.8534)	(0.0489)	(-0.6535)	(-0.7842)	(-3.3773)	(-3.8780)

Panel C: Equally Weighted Decile

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10 - Q1
Excess	0.0097**	0.0095*	0.0088*	0.0096*	0.0090*	0.0094*	0.0088*	0.0087*	0.0089*	0.0079	-0.0018**
Return	(2.0951)	(1.9457)	(1.8220)	(1.9515)	(1.8864)	(1.9593)	(1.7845)	(1.7501)	(1.7326)	(1.6066)	(-2.0061)
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10 - Q1
3-Factor	0.0006	0.0003	-0.0004	0.0002	-0.0000	0.0000	-0.0005	-0.0011	-0.0008	-0.0018*	-0.0018**
Alpha	(0.7521)	(0.3559)	(-0.4836)	(0.1988)	(-0.0522)	(0.0224)	(-0.6068)	(-1.1838)	(-0.8571)	(-1.9411)	(-2.0061)
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10 - Q1
5-Factor	0.0011*	0.0008	0.0001	0.0006	0.0007	0.0002	0.0001	-0.0008	-0.0003	-0.0015*	-0.0026***
Alpha	(1.7180)	(1.0551)	(0.1026)	(0.7579)	(0.9582)	(0.3642)	(0.0744)	(-1.0071)	(-0.4046)	(-1.8844)	(-3.0944)

Panel D: Value Weighted Decile

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10 - Q1
Excess	0.0131***	0.0110***	0.0091**	0.0079*	0.0073*	0.0071*	0.0067	0.0081**	0.0059	0.0067*	-0.0064***
Return	(3.1932)	(2.7401)	(2.2597)	(1.9707)	(1.8619)	(1.6879)	(1.6467)	(2.0076)	(1.3944)	(1.6808)	(-3.6985)
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10 - Q1
3-Factor	0.0042***	0.0022	0.0009	-0.0003	-0.0012	-0.0020*	-0.0014	-0.0009	-0.0033***	-0.0026**	-0.0068***
Alpha	(2.9654)	(1.5778)	(0.7033)	(-0.2563)	(-1.1651)	(-1.8993)	(-1.1904)	(-0.8149)	(-3.1516)	(-2.4540)	(-3.7704)
	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10 - Q1
5-Factor	0.0048***	0.0026*	0.0008	0.0001	-0.0009	-0.0019*	-0.0013	-0.0000	-0.0026***	-0.0030***	-0.0078***
Alpha	(3.4588)	(1.8491)	(0.6583)	(0.0750)	(-0.8735)	(-1.8203)	(-1.1026)	(-0.0237)	(-2.6471)	(-2.9335)	(-4.3795)

Table III: Characteristics of Quintile Portfolios

This table reports the *Size,* the log of the market value of equity, *Monthly Turnover,* and *Moving Targets*, of the five quintile portfolios.

	Q1	Q2	Q3	Q4	Q5
Size	6543374	8200199	8337254	8259805	8419977
Monthly Turnover	0.1837737	0.23842	0.2467544	0.2359856	0.1881331
Moving Targets	0.3989665	0.5026246	0.5601085	0.6176733	0.722707

Table IV: Main Results – Fama-MacBeth Regressions

This Table reports the Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on *Moving Targets* and a host of known return predictors. *Size* is log of market value of equity, *log(BM)* is log book value of equity over market value of equity, R*et(-1,0)* is previous month's return, and R*et(-12, -1)* is the cumulative return from month -12 to month -1. *SUE* is the standardized unexpected earnings and computed as actual earnings per share minus average analyst forecast earnings per share, divided by the standard deviation of forecasts. *t*-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)	(3)
		Ret	
Moving Targets	-0.0056***	-0.0059***	-0.0059***
	(-2.8969)	(-3.1951)	(-3.2397)
Size		0.0007**	0.0007**
		(2.0435)	(2.0476)
Log(BM)		-0.0638	-0.0492
		(-0.5408)	(-0.4326)
Ret(-1, 0)		-0.0167***	-0.0171***
		(-2.7213)	(-2.7759)
Ret(-12,-1)		0.0002	-0.0002
		(0.0801)	(-0.0584)
SUE			0.0133**
			(2.4792)
R-Squared	0.0008	0.0295	0.0309
N	369248	369248	369248

Table V: Target Persistence

This Table reports the Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on *Moving Targets,* separately for firms with high persistent and low persistent target sets and a host of known return predictors. *Size* is log of the market value of equity, *log(BM)* is log of the book value of equity over the market value of equity, *Ret(-1,0)* is the previous month's return, and *Ret(-12, -1)* is the cumulative return from month -12 to month -1. *SUE* is the standardized unexpected earnings and computed as actual earnings per share minus average analyst forecast earnings per share, divided by the standard deviation of forecasts. *t*-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)
	High persistent Targets	Low persistent Targets
	Ret	
Moving Targets	-0.0149***	-0.0009
	(-4.4185)	(-0.2668)
Size	0.0010***	0.0010***
	(2.8656)	(3.0192)
Log(BM)	-0.1752	-0.7974
	(-0.4694)	(-1.2948)
Ret(-1, 0)	-0.0132**	-0.0170***
	(-2.1170)	(-2.9631)
Ret(-12,-1)	0.0008	0.0001
	(0.2947)	(0.0604)
SUE	0.0136*	0.0253***
	(1.7837)	(2.6757)
R-Squared	0.0540	0.0584
N	186466	183624

Table VI: Complexity of Target Sets

This Table reports the Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on *Moving Targets,* separately for firms with complex and simple target sets. and a host of known return predictors. *Size* is log of the market value of equity, *log(BM)* is log book value of equity over the market value of equity, *Ret(-1,0)* is the previous month's return, and *Ret(-12, -1)* is the cumulative return from month -12 to month -1. *SUE* is the standardized unexpected earnings and computed as actual earnings per share minus average analyst forecast earnings per share, divided by the standard deviation of forecasts. *t*-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)
	Complex Target Set	Simple Target Set
	Ret	
Drop Targets	-0.0106***	-0.0030
	(-3.7212)	(-1.1713)
Size	-0.0001	0.0003
	(-0.2269)	(0.8118)
Log(BM)	-0.0010*	-0.0012*
	(-1.7538)	(-1.7884)
Ret(-1, 0)	-0.0135*	-0.0161***
	(-1.7894)	(-2.6929)
Ret(-12,-1)	-0.0022	0.0009
	(-0.6423)	(0.3694)
SUE	0.0329*	-0.0239
	(1.9281)	(-0.8182)
R-Squared	0.0540	0.0584
N	175873	182097

Table VII: Financial vs Non-Financial Targets

This Table reports the Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on *Moving Targets,* and a host of known return predictors. *Size* is log of the market value of equity, *log(BM)* is the log book value of equity over the market value of equity, *Ret(-1,0)* is the previous month's return, and *Ret(-12, -1)* is the cumulative return from month -12 to month -1. *SUE* is the standardized unexpected earnings and computed as actual earnings per share minus average analyst forecast earnings per share, divided by the standard deviation of forecasts. *t*-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1)	(2)
	Non-Financial Targets	Financial Targets
	Ret	
Moving Targets	-0.0046***	-0.0027*
	(-2.6671)	(-1.7431)
Size	0.0007**	0.0007**
	(2.0791)	(2.1007)
Log(BM)	-0.2586	-0.2625
	(-0.9074)	(-0.9286)
Ret(-1, 0)	-0.0144**	-0.0143**
	(-2.3813)	(-2.3512)
Ret(-12,-1)	0.0002	0.0002
	(0.0839)	(0.0574)
SUE	0.0224***	0.0214***
	(3.4266)	(3.2935)
R-Squared	0.0326	0.0328
N	373334	373334

Table VIII: Analyst Interaction

This Table reports the Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on *Moving Targets,* and a host of known return predictors. *Size* is log of the market value of equity, *log(BM)* is log book value of equity over the market value of equity, *Ret(-1,0)* is the previous month's return, and *Ret(-12, -1)* is the cumulative return from month -12 to month -1. *SUE* is the standardized unexpected earnings and computed as actual earnings per share minus average analyst forecast earnings per share, divided by the standard deviation of forecasts. *t*-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	(1) Targets in Presentation	(2) Targets in Presentation + Analysts Q&A	(3) Targets in Presentation + Analysts Q&A + CEO Answers
		Ret	
Moving Targets	-0.0062***	-0.0056***	-0.0032
	(-3.3593)	(-3.0003)	(-1.3367)
Size	0.0011***	0.0007*	-0.0005
	-3.4187	-1.9372	(-1.0895)
Log(BM)	-0.0286	-0.3081	-0.0021***
	(-0.2237)	(-1.0518)	(-3.1776)
Ret(-1, 0)	-0.0184***	-0.0138**	-0.0156**
	(-3.0877)	(-2.2810)	(-2.0677)
Ret(-12,-1)	0.0006	0.0003	-0.0005
	-0.2283	-0.1108	(-0.1570)
SUE	0.0047	0.0199***	0.0301**
	-1.1299	(2.9212)	(2.0926)
R-Squared	0.0309	0.0332	0.031
N	391368	373568	338630

Table IX: Value Weighted Decile Portfolios for the Most Persistent Targets

This Table reports the calendar-time portfolio returns. We compute decile portfolios based on the prior year's distribution of *Moving Targets* across all stocks, where we restrict targets to only the top persistent Targets. Stocks then enter the decile portfolios in the month after each earnings conference calls. Stocks are held in each decile portfolio until the next earnings conference call. We report Excess Returns (return minus risk-free rate), Fama-French 3-factor Alphas (market, size, and value), and 5-factor Alphas (market, size, value, momentum, and liquidity). *Panel A* reports equal-weight quintile portfolio returns, *Panel B* reports value-weight quintile portfolio returns, *Panel C* reports equal-weight decile portfolio returns, *Panel B* reports value-weight decile portfolio returns. *t*-statistics are shown below the estimates, and statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q10 - Q1
Excess Return	0.0140***	0.0114***	0.0104**	0.0074*	0.0086**	0.0077*	0.0073*	0.0084**	0.0065	0.0064	-0.0076***
	(3.2500)	(2.8332)	(2.5704)	(1.8544)	(2.0910)	(1.8505)	(1.7889)	(1.9876)	(1.5313)	(1.5570)	(-3.4562)
3-Factor Alpha	0.0052***	0.0024	0.0020	-0.0005	-0.0004	-0.0008	-0.0009	-0.0008	-0.0025**	-0.0030**	-0.0081***
	(3.0797)	(1.5173)	(1.3641)	(-0.3329)	(-0.2728)	(-0.5596)	(-0.6806)	(-0.5756)	(-2.0052)	(-2.0676)	(-3.6411)
5-Factor Alpha	0.0060***	0.0023	0.0016	-0.0002	-0.0001	-0.0005	-0.0006	0.0000	-0.0022*	-0.0039***	-0.0099***
	(3.5183)	(1.4318)	(1.0900)	(-0.1593)	(-0.0629)	(-0.3651)	(-0.4541)	(0.0145)	(-1.7257)	(-2.8833)	(-4.3978)