Predicting Anomalies

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ABSTRACT

We show that stock returns exhibit predictable patterns before the publication of anomaly trading signals. Moreover, anomaly trading signals derived from financial data are themselves predictable, making it possible to trade before financial statements are released. A trading strategy based on predicted anomaly signals earns an annualized return of 2.80% in the quarter before the signal is released. In recent periods, this return predictability is concentrated in signals that are harder to forecast, and returns are increasingly earned several quarters before signals are released. Our findings suggest anomalies are more anomalous than previously recognized.

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JEL Classification Numbers: G12, G14

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Asset pricing anomalies are trading signals that predict future abnormal returns.[1] For anomalies based on annual financial data, these returns are largest in the period immediately *after* the release of financial statements and decay quickly thereafter.[2] Yet, the literature has largely overlooked the period *prior* to the release of anomaly trading signals. In this paper, we show that anomaly returns exhibit predictable patterns in the weeks and months before anomaly signals are publicly released. We also show that anomaly signals are highly predictable, making it possible to trade before the signal is publicly revealed.

Figure 1 displays our first key result. Although Bowles et al. (2024) show that anomaly returns are concentrated in the weeks immediately following the release of anomaly signals (starting at $t = 0$), we show that returns are predictable *before* information is released. In other words, prices respond to anomaly signals even before the signals are publicly known. How is this possible? How can the market incorporate information before it has been publicly released? The answer is simple: many anomaly signals are highly predictable.

[Figure 1 about here.]

To study this predictability, we examine several anomaly prediction models, ranging from a sophisticated machine learning model to autoregressive models to a simple martingale model. Surprisingly, the simple martingale model of the form $E[x_{t+1}] = x_t$ often outperforms more complex models. Using the asset growth anomaly (Cooper et al. (2008)) as an example, we show that asset growth measured using third-quarter financial statements is a reliable predictor of annual asset growth measured using annual financial statements. This suggests that it is possible to trade the asset growth anomaly (and other anomalies) early, a result

[1] As noted in Brennan and Xia (2001), "An asset pricing anomaly is a statistically significant difference between the realized average returns associated with certain characteristics of securities, or on portfolios of securities formed on the basis of those characteristics, and the returns that are predicted by a particular asset pricing model."

[2] Bowles et al. (2024) show that the returns to many anomalies are increasingly concentrated in the period immediately after the public release of new information about anomaly trading signals. Ivkovic and Zekhnini (2024) show that this change in return patterns tends to start once academic research first documents a particular anomaly.

that calls into question the very manner in which researchers define and measure asset pricing anomalies.

To analyze whether anomaly returns exhibit predictable patterns prior to the release of annual financial statements and anomaly signals, we adopt a perfect foresight model which assumes that an anomaly signal is perfectly predictable one quarter before its release. We then examine the returns to long-short anomaly portfolios around the release of the anomaly signals.[3] However, instead of examining return patterns in the days, weeks, and months after the release of key financial data, we examine returns in the days, weeks, and months *before* the release of key financial data. We find that having perfect foresight and trading one quarter before the anomaly signal is released yields an additional return of 171 basis points for the average anomaly, or 7.10% on an annualized basis. Moreover, having perfect foresight and trading one month ahead (instead of one quarter ahead) earns 120 basis points (20.4% annualized), indicating that the results are strongest in the period immediately before the information is released.

Of course, since no trader has a crystal ball to perfectly predict future financial data and anomaly signals, it is not clear whether investors could take advantage of these return patterns. Accordingly, we also analyze whether anomaly signals are predictable themselves. We show that they are. To show this, we test four different models to predict anomaly signals and the constituents of anomaly portfolios: a first-order autoregressive model that predicts the level of a stock's anomaly signal (AR Signals), a first-order autoregressive model that predicts the relative ranking of a stock's anomaly signal (AR Rankings), a machine learning model that uses a stock's past anomaly signals and relative rankings to predict anomaly portfolio inclusion (ML), and a martingale model that assumes that the relative ranking of a stock's anomaly signal next period is equal to its relative ranking this period.

[3]We use event time tests to examine return patterns around the release of anomaly signals. This requires anomalies that exclusively use information that arrives at infrequent, discrete, and observable points in time. Accordingly, we focus on the 28 anomalies used in Bowles et al. (2024) and which rely on information released in either earnings announcements or 10-K filings. See Section II for details.

The results from all four of these prediction models point to the same conclusion: most of the anomalies we study are highly predictable. For each anomaly and prediction method, we calculate the model's F1 Score,[4] which is analogous to the percent of observations predicted correctly. In general, the two autoregressive models underperform the other two models, though they both still yield F1 Scores well above 60% for most anomalies. In other words, the worst- performing models are still able to accurately predict annual anomaly signals one period ahead more than 60% of the time. However, since autoregressive models impose a linear structure, they seem to perform poorly when predicting which stocks will be in the extreme deciles (i.e., the long and short deciles).

In comparison, the machine learning model and the martingale model are consistently more accurate. Across all 28 anomalies and across our three-decade sample period, the F1 Score for both models averages 72%, meaning the models make correct predictions 72% of the time. The success of the martingale model in particular is not only surprising but also indicates that anomaly signals are highly persistent. For the average anomaly, most of the stocks with high and low anomaly signals after the third quarter (Q3) still have high and low anomaly signals after the fourth quarter (Q4). Thus, a long-short anomaly portfolio constructed at Q3 will remain largely unchanged when annual information is released at Q4. Specifically, 66% of the annual portfolio's stocks are holdovers from the portfolio constructed at Q3. In other words, by simply assuming persistence of anomaly signals from Q3 to Q4, a trader could make portfolio assignments one quarter early and be correct approximately two-thirds of the time.

Interestingly, we find that the level of persistence is heterogeneous across anomalies; some accounting numbers and anomaly signals are highly persistent, while others are not. For example, for the Asset Turnover and the Profit Margin anomalies, we find that over 85% of the stocks in the annual portfolio are holdovers from Q3. As a result, our prediction models

[4]The F1 Score is a measure of model accuracy that balances Type 1 and Type 2 errors. See Section A of the Internet Appendix for details on the F1 Score and related issues.

perform well for these two anomalies – the F1 Scores are around 90%. On the other hand, only 26% of the stocks in the annual Earnings Surprise anomaly portfolio were also in the portfolio at Q3 and our prediction models perform poorly for this anomaly; the martingale model has an F1 Score of just 29%. We find that the Revenue Surprise anomaly is similarly difficult to predict. Of course, it is not surprising that our prediction models have difficulty with these two anomalies since they are, by definition, constructed to be "surprises."

Given the success of the machine learning model and the martingale model, we further examine their Type 1 (false positive) and Type 2 (false negative) error rates and study their forecast accuracy through time by charting F1 Scores for each anomaly and year in our sample. We find that both models are consistently accurate and have low error rates. Of course, the machine learning model could not have been implemented in the early years of our sample, so one advantage of the martingale model is that any trader could have easily implemented it throughout our entire sample period.

We then examine whether these prediction models can be used to earn abnormal returns even before anomaly signals are publicly released. In short, we find that they can. For the average anomaly, constructing anomaly portfolios three months *before* annual information releases using the simple martingale model results in additional abnormal returns of 70 basis points (or 2.80% on an annualized basis). These are *additional returns* since they are in addition to the returns earned from trading on the anomaly after the anomaly signal information becomes public.

While the returns to trading early using the martingale model are economically significant, they are less than half of those from the perfect foresight model, which earns 171 basis points (7.10% annualized) over the same three-month period. Why is there such a large difference? Put differently, if the perfect foresight model earns large returns and our prediction models are highly accurate, then why are the returns from trading using the prediction models so much less than the returns from the perfect foresight model?

We investigate this by examining the returns to correct predictions, false positives, and false negatives.[5] With respect to correct predictions, together they earn 127 basis points in the three months prior to the release of annual anomaly signals. In contrast, a portfolio of false positive predictions (Type 1 errors) *loses* 60 basis points in the same three months. Perhaps even more interestingly, a portfolio of false negative predictions (Type 2 errors) earns an astonishing return of 297 basis points in the three months before annual information releases (12.42% annualized). This return is four times that of the martingale model and nearly double that of the perfect foresight model. This finding suggests that the stocks that were not expected to be in the annual long-short anomaly portfolio (but actually are ex-post) earn incredibly large returns.

This finding is even more striking when we zoom in on just the one week before annual information releases and see that the martingale model earns 27 basis points, the perfect foresight model earns 69 basis points, yet the portfolio of false negative predictions earns 108 basis points (74.82% annualized). Thus, returning to the question just posed, the reason the martingale model and the machine learning model underperform the perfect foresight model is that incorrect predictions may be rare, but they are incredibly costly.

Finally, we also study whether the returns to predicting anomalies and trading early have changed over time. The results are three-fold. First, returns to trading prior to annual information release have diminished in recent years. During the early part of our sample (1990-2006) the perfect foresight model earns 279 basis points on the average anomaly over the three months before annual information releases. In recent years (2007-2023), the perfect foresight model earns only 92 basis points.

Second, though the martingale and machine learning models are consistently accurate over our entire sample period, the returns from trading based on these models have been

[5]False positives are those stocks that were predicted to be in the annual long-short anomaly portfolio and were *not* in the annual anomaly portfolio after the signal was publicly released (i.e., Type 1 errors). False negatives are stocks that were not predicted to be in the annual anomaly portfolio but were in the annual portfolio when the signal was released (i.e., Type 2 errors).

arbitraged away in recent years. In the early years of our sample, trading three months early using either model earns approximately 200 basis points. In the recent period, the martingale model loses 19 basis points while the machine learning model loses 7. These findings suggest investors are using prediction models (perhaps models similar to ours) to arbitrage away predictable returns in the quarter before annual information is released.

Third, correct predictions are less profitable in recent years while incorrect predictions are even more costly. Indeed, false negative predictions earn a much larger share of returns from trading prior to annual information releases. This finding suggests that investors have arbitraged away the predictable component of anomaly returns, but not the difficult to predict component. Interestingly, we also find that although returns to trading three months early have been arbitraged away in recent years, there are still predictable returns to trading *six* months early using a two quarter ahead martingale model. In other words, predicting anomalies can still be profitable, but you need to act even earlier in event time. This is consistent with Greenwood and Sammon (2022) who show that index addition and deletion premiums have moved earlier and earlier in event time as a result of arbitrage competition.

Our paper contributes to several strands of the literature. First, we contribute to the long-running debate on the nature and existence of anomalies. While several papers debate whether anomalies are the result of data mining or unmeasured costs (e.g., Hou et al. (2020) and Chen and Velikov (2023)) or whether anomalies are real and the result of mispricing (e.g., Chen and Zimmermann (2019), Chen and Zimmermann (2021), and Jensen et al. (2021)), our findings provide strong evidence that anomalies are really in the data and that they are related to information about anomaly signals. These results shed important light on the economic mechanism underlying many asset pricing anomalies.

Second, our paper relates to the large literature on the response of capital markets to the release of accounting data (starting with Ball and Brown (1968)). In this sense, our work contributes to the broader literature on the private versus social value of information releases (e.g., Hirshleifer (1971)). Our paper adds to this literature by generating a new question:

if traders are investing time and capital to predict anomalies, are they over-investing in information acquisition relative to the social optimum?

Finally, our paper also contributes to the extensive literature on market efficiency. The existence of publicly available information that predicts stock returns has long bothered financial economists because these so-called anomalies are apparent violations of market efficiency. We show that the violations are happening at a *deeper level* because the public information that predicts returns is itself predictable based on previously released public information. As a consequence, our results show that anomalies are more anomalous than previously realized.

In addition to these contributions, our results have a number of important implications. First, it is important to understand *when* returns are earned because timing impacts our measurement and economic interpretation of events. Second, our findings show that the returns to many anomalies have migrated over time and are now more concentrated around important information releases. As a result, the returns to many anomalies are larger than they initially appear when rebalancing using older methods.[6] Third, our findings have important implications for factor models. If returns are earned prior to information releases, then existing research may be mismeasuring factor returns. This mismeasurement could have implications for our models of risk and the subsequent interpretations we assign to abnormal returns.

The rest of the paper proceeds as follows. Section I provides background to motivate our empirical tests. Section II discusses our data and the construction of the anomaly variables. Section III presents our main findings that anomalies are predictable, and this information can be used to generate abnormal returns. Section IV concludes.

[6]See Bowles et al. (2024) and Ivkovic and Zekhnini (2024). See also Asness and Frazzini (2013) who show that the HML factor performs better if the calculation is updated to condition on more recent price data.

I. Background

Our study relates to several lines of research that examine anomalies based on accounting information. First, it links to the stream of papers that examine the existence, magnitude, and explanations of accounting-related anomalies (e.g., for surveys of this literature, see Kothari (2001); Lee (2001); Richardson et al. (2010); and Lee et al. (2015), among others). As noted in Lee et al. (2015), explanations for accounting-related anomalies are often tied to their connections with attributes of the firm, its performance, or its information environment. These attributes can include such factors as the cheapness of the stock (e.g., Fama and French (1992), Lakonishok et al. (1994)), the profitability of the stock (e.g., Piotroski (2000)), or the safety of the stock (as measured by leverage or financial distress (Dichev (1998); Campbell et al. (2008))). Indeed, Asness et al. (2019) pull these attributes together to create a quality score for stocks that are safe and profitable, demonstrating that these accounting information signals are associated with predictable returns.

Perhaps most related to our paper are those that examine the quality of accounting information and its relation to future earnings or future stock returns. Most accounting numbers involve some amount of judgment, discretion, and estimation, all of which are susceptible to human error or human manipulation. For example, Sloan (1996) documents the differential persistence of accruals versus cash flows – accruals require more estimation and managerial discretion, which is likely related to accruals having lower persistence. Both Sloan (1996) and Xie (2001) show that this feature of accrual-based accounting numbers appears to be unanticipated and even mispriced by investors.

Further, Richardson et al. (2005) show that the less reliable components of accruals (i.e., those with greater propensity for manager discretion or manipulation) are less persistent and that investors fail to appreciate this differential reliability, leading to significant mispricing. In addition, Fairfield et al. (2003) provide evidence that investors tend to misunderstand the growth embedded in accruals. Overall, the evidence in this line of research suggests that the persistence of certain accounting numbers helps explain mispricing of some accounting information. In a similar spirit, we show that investors seem to act as if they do not anticipate the persistence of a large number of accounting anomalies, leading to predictability in the anomaly portfolio assignment and significant mispricing.

Second, this study relates to a long literature on market reactions to the release of information. Samuelson (1965) famously proved that price changes should be unpredictable if they properly reflect all available information: "If one could be sure that a price will rise, it would have already risen." A number of papers test this idea and the empirical evidence shows that since at least the 18th century, public equity markets have focused on the arrival of new information.[7] Indeed, the arrival of new information creates a race to trade on it as quickly as possible. Going all the way back to Fama et al. (1969), researchers have documented that share prices move around the time that information is released.[8]

However, in the subsequent decades, researchers have documented that share prices continue to update and change in the weeks, months, and even years after information is released. The first accounting-based anomaly identified by researchers is post-earnings announcement drift (PEAD) (e.g., Ball and Brown (1968), Bernard and Thomas (1989), and Bernard and Thomas (1990)). The signature pattern of post-earnings announcement drift is the tendency of stock prices to continue moving in the direction of recently released earnings news.[9] As noted in Richardson et al. (2010), post-earnings announcement drift can be summarized as investors underestimating the implications of current earnings for future earnings. A similar intuition applies in our setting: we show investors appear to underestimate the implications of current anomaly signals for future anomaly signals. Indeed, as discussed in Gabaix (2019),

[7]Koudijs (2016) examines how shares in English companies traded on the Amsterdam exchange in the 1700s responded to new information via the arrival of ships from England.

[8]Most recently, Hartzmark and Solomon (2024) show that aggregate stock market returns move in a predictable manner due to price pressure from investors trading to capitalize on recently announced dividend payments.

[9]Researchers have since documented other forms of drift or momentum to dividend announcements and stock splits (e.g., Ikenberry and Ramnath (2002)).

under-reaction to news can occur when investors are inattentive to the true auto-correlation of a stochastic time series.

Third, our study links to the literature examining the predictability of accounting information using prior information. A very early literature examines the time-series properties of earnings, considering whether earnings tend to follow a random-walk model and exhibit mean reversion (e.g., Kothari (2001)). Fama and French (2000) use a cross-sectional approach to earnings prediction and present evidence that profitability is mean-reverting (about 38% per year). Beyond that early evidence, multiple studies demonstrate that a broad set of accounting variables can predict future returns (e.g., Lev and Thiagarajan (1993); Abarbanell and Bushee (1997), Abarbanell and Bushee (1998)). Despite decades of research examining the basic predictability of future earnings/returns using current earnings or accounting information, our study offers a simple but important distinction. Where our study is different is that we rewind the clock to the period prior to the information's release, examining whether anomaly signals can be predicted before they are even publicly released.

Building on Samuelson (1965), we examine whether accounting information used to form anomalies is "properly anticipated."[10] If it is, then stock returns should not exhibit predictability in the period prior to the release of accounting information about the anomaly signal.

Our empirical design tests this simple idea using a simple methodology: event studies. While there is a large literature debating the concept of market efficiency, there is also a large literature critiquing the validity of many empirical designs used to test for market efficiency. But as noted in Fama (1991), "The cleanest evidence on market-efficiency comes from event studies, especially event studies on daily returns. When an information event can be dated precisely and the event has a large effect on prices, the way one abstracts from expected returns to measure abnormal daily returns is a second-order consideration. As a result,

[10]Samuelson (1965) titled his article "Proof That Properly Anticipated Prices Fluctuate Randomly."

event studies can give a clear picture of the speed of adjustment of prices to information." Our paper uses event studies to test whether prices react even before information is released.

II. Data, Anomaly Selection, & Anomaly Calculations

Our study relies on several key data sources. First, we use daily stock returns from the Center for Research in Security Prices (CRSP). From CRSP, we also collect prices, trading volume, and shares outstanding. Second, we use Compustat to collect firms' quarterly and annual financial information to calculate anomaly variables. Third, we use the Compustat Snapshot database to identify point-in-time information releases, as discussed below.

A. Compustat Snapshot

Key to our study is identifying when anomaly-relevant information is first made available to investors. To do this, we rely on Compustat Snapshot (hereafter, "Snapshot"), a database that records when accounting information about a firm was made publicly available.[11] As noted in D'Souza et al. (2010), different financial statement line items are released at different times by different companies. Thus, for each line item on every financial statement, Snapshot helps identify when the line item was first publicly released. For example, Snapshot identifies whether the book value of assets was revealed on the earnings announcement date or at the 10-K filing date for a given firm and for a given fiscal year and quarter. Using Snapshot, we are able to determine – at the anomaly level, the firm level, and the quarter level – the earliest date at which anomaly-relevant information is publicly known. We use Snapshot to identify anomaly signals for all quarterly information releases.

[11]Point in time data has also been used in several recent studies to evaluate departures of market price from fundamental value (Bartram and Grinblatt (2018), Bartram and Grinblatt (2021)) and to evaluate the timing of anomaly returns (Bowles et al. (2024), Ivkovic and Zekhnini (2024)).

Our sample period begins in January 1990 and runs through 2023. Snapshot data identify information release dates beginning in the mid-1980s. We begin the sample in 1990 to allow for several anomalies that use multiple years of data in their construction.[12]

B. Anomaly Selection

Given our focus on anomaly returns before and after the release of financial information, we use a set of anomalies for which we can clearly observe the timing of the release of anomaly signals. Although our starting point is the 97 anomalies examined in McLean and Pontiff (2016), for many of these 97 anomalies the underlying data change constantly, making it difficult to establish a discrete information release date.[13] Accordingly, as in Bowles et al. (2024), we focus on the subset of anomalies that depend entirely on information that has a precise revelation date.

We refine the list of anomalies in McLean and Pontiff (2016) by requiring each anomaly to be based entirely on information that is publicly revealed in quarterly financial statements (10-Ks or 10-Qs) or related releases (such as press releases around earnings announcement dates). The resulting sample contains 28 accounting-based anomalies. For each anomaly, we use Snapshot to identify the earliest date such that all information necessary to construct the anomaly signal is known. We call this date the *information release date*.[14]

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[12] For more details on Snapshot see Section B of the Internet Appendix. Also see Bowles et al. (2024).

[13] For example, the earnings-to-price ratio (Basu (1977)) requires two data points for each stock: earnings and price. While annual earnings data are released on clearly identified dates and generally remain unchanged for the year, prices change constantly, making it difficult to define the precise information release date for this anomaly. Thus, we do not include earnings-to-price ratio in our study. In contrast, asset growth (Cooper et al. (2008)) is measured using only book assets, a value that is revealed at clear points in time and does not change frequently, so we include asset growth in our sample.

[14] For some composite measures based on multiple pieces of information, we use the latest information release date. For instance, to compute asset turnover, which requires sales, cash, long-term debt, short-term debt, common and preferred book equity, and minority interest, we use the latest information release date for those variables as the information release date for the anomaly. If sales is revealed on Monday in an earnings announcement but the other variables are not revealed until Wednesday in the 10-K filing, the anomaly variable cannot be calculated until Wednesday. Thus, for this example, Wednesday would be the information release date. For further details on these anomalies and their construction in the original papers, see Section C of the Internet Appendix.

C. Anomaly Calculations

Anomaly variables are generally constructed based on the paper originally citing the anomaly.[15] However, we adjust the calculations for some of the anomalies since most of them are constructed using annual financial data while our study uses quarterly anomaly signals to predict annual anomaly portfolios. Specifically, the construction of anomalies that rely on revenue or earnings or other flow variables has been adjusted to use the year-to-date or end-of-quarter financial information. For example, the Asset Turnover anomaly is traditionally calculated by dividing annual sales by year-end net operating assets. In this study, we calculate Asset Turnover quarterly by dividing year-to-date sales by net operating assets as of the end of Q3. Thus, the Asset Turnover value for a firm after the third quarter financial statements are released is a measure of year-to-date Asset Turnover.

We also use the year-to-date construction for anomalies that are based on changes in stock variables, such as the Asset Growth anomaly. In these cases, prior research using an annual anomaly signal would compare last year's annual financial statements to this year's. However, to calculate these anomalies on a quarterly basis, we do not do a year-over-year or quarterly comparison, but instead maintain the year-to-date approach. For example, asset growth measured after the release of third quarter financial statements is calculated by comparing total assets at the end of the third quarter to total assets as of the end of last year, capturing the year-to-date growth in assets.

It is worth mentioning here that the focus of this study is to analyze how well past anomaly signals predict future annual anomaly signals. In our view, using the year-to-date approach to calculate quarterly anomaly signals will provide better predictors. This is because quarterly year-to-date predictors will take into account all available information since the prior year end to forecast the coming year's anomaly signal. That is, an investor wishing to predict a certain anomaly signal in next year's annual report would likely use

[15] We also verify the construction of these 28 anomalies with the code provided by Andrew Chen and Tom Zimmerman on www.OpenSourceAssetPricing.com and discussed in Chen and Zimmermann (2022).

all the information available to them at the time of the prediction – hence the intuition for using the quarterly and year-to-date information in predicting future signals. [16]

Overall, we construct and analyze a panel of observations for each anomaly, firm, and year. For a given firm-year, we measure the values of the annual anomaly signal, the quarterly anomaly signal for Q3 and Q2, and the annual anomaly signal from the prior year, $Q4_{t-1}$. Each observation also records several important dates, especially the information release date. We extend the panel by incorporating daily returns and, for consistency, limiting the sample to firms with December fiscal year ends. In all our tests, we follow the standard methodology of considering anomaly portfolios to include the stocks in the top and bottom deciles for each anomaly. Summary statistics for our sample are detailed in Table I.

[Table 1 about here.]

III. Return Patterns and Signal Predictability

This section progresses in three stages as we detail our analyses and key findings. First, we describe abnormal return patterns to anomalies in the months before annual information releases. Next, we examine the predictability and persistence of anomaly signals and anomaly portfolios. Finally, we study whether models to predict anomaly signals can be used to generate abnormal anomaly returns in the months before the release of annual information.

A. *Anomaly Returns Before Information Release Dates*

A fundamental tenet of the efficient markets hypothesis (EMH) is that prices should react quickly to the release of new and relevant information and that prices should not continue moving in a predictable direction after the information is released.[17] We consider a separate

[16] We have also performed much of the analysis in this study using an alternative year-over-year approach to calculating quarterly anomaly values. This approach resulted in lower predictive power; however, the main inferences of the paper remained unchanged.

[17] This latter idea is at the center of the post-earnings-announcement drift anomaly.

notion related to the EMH – prices should not move in a predictable direction *before* the release of new and relevant information. We test this idea by examining return patterns immediately before information release dates.

To do this, we use an event-time approach that tracks stock returns in the 60 trading days (three months) before annual information release dates (e.g., Bowles et al. (2024)). This technique mimics a hypothetical investor who is endowed with perfect foresight about future anomaly signals. The investor then forms anomaly portfolios based on annual financial information one quarter before that information is publicly released. Based on that intuition, we compute perfect-foresight returns for a portfolio of all 28 accounting-based anomalies in our sample, which we label as the Average anomaly portfolio. The results of trading anomalies with perfect foresight are shown in Figure 1 and Table II.

[Table 2 about here.]

Figure 1 shows the return profile for the Average anomaly from three months before to three months after the information release date. Most relevant for this study is the return profile *before* the information release date – the figure shows significant returns to trading early with perfect foresight. Table II provides returns to the event-time, perfect-foresight strategy over various periods. It shows that trading three months before information release dates yields a return of 171 basis points (7.10% on an annualized basis). This is slightly less than the return earned after information release dates (178 basis points or 7.70% annualized).

Not only are the returns to perfect foresight and trading early high, but they are also highly concentrated in the weeks nearest the information release date. This can be clearly seen in Figure 1 and in Table II, in which having perfect foresight earns 2.8 basis points per day over the three months before the information release dates, 5.7 basis points per day over the one month before, and 11.5 basis points per day over the one week before. These results are striking as they challenge the intuition that has prevailed in the literature since at least Fama et al. (1969): that the time of the information release is the appropriate time at which stock prices should begin to change. Instead, these findings show returns move predictably prior to information releases, and this predictability strengthens as information releases near. That is, the results in Figure 1 and Table II present evidence of a *pre*-information announcement drift, suggesting that abnormal returns to anomaly signals begin even before the anomaly signal is publicly known.

This raises two important questions. First, to what extent are anomaly signals predictable? That is, can market participants incorporate information about anomalies before the information is publicly released? Second, is it possible to implement a prediction model and capture some of the returns earned before information release dates? We examine these questions in the next section.

B. Anomaly Signal Persistence

Table III shows the temporal correlation of anomaly signals for the 28 anomalies in our sample and for the Average anomaly. The table shows the pairwise correlations between the annual anomaly signal ($Q4_t$) and the anomaly signals calculated one quarter earlier ($Q3_t$), two quarters earlier ($Q2_t$), and one year earlier ($Q4_{t-1}$). In addition, we provide serial correlations for anomaly decile rankings within year. These analyses provide a simple examination of the extent to which anomaly signals and anomaly portfolio assignments are predictable.

[Table 3 about here.]

In general, Table III shows that anomaly signals exhibit positive serial correlation. The Average anomaly at ($Q4_t$) is correlated at 0.41 with the Average anomaly calculated one quarter earlier ($Q3_t$) Q4 is correlated at 0.41 However, the correlations weaken as the time between anomaly signals increases. The correlation of annual anomaly signals with ($Q2_t$) anomaly signals is 0.31 while the correlation with last year's annual anomaly signal ($Q4_{t-1}$) is 0.05.

There is also significant variation in anomaly signal correlations across anomalies. The Asset Growth (Ag) anomaly, for example, has a correlation of 0.94 between the annual signal

(Q4) and the signal at Q3. Other anomalies also have high correlations, such as Inventory Growth (Ig), Changes in Net Working Capital (Nwc), Profit Margin (Pm), and Sales Growth (Sg). On the other hand, other anomalies exhibit fairly low serial correlation, including Asset Turnover (At), Net Operating Assets (Noa), Non-current Operating Assets (Nca), Percent Operating Accruals (Pta), Return on Equity (Roe), and Taxes (Tx). Overall, while anomaly signals are serially correlated on average, there is variation in the strength of that correlation across anomalies.

The serial correlations improve for the *relative ranking* of anomaly signals, which is necessary for portfolio construction (i.e., the typical long-short portfolio is based on relative rankings). The rightmost columns of Table III show that the temporal correlations between anomaly signal rankings are much higher than the correlations between raw anomaly signals. The Average anomaly has a correlation coefficient of 0.81 between the ranking in Q3 and the ranking in Q4. Even the correlations between Q2 and Q4 are high; 0.71 for the Average anomaly. And, with respect to the variation across anomalies, it is striking that 20 out of the 28 anomalies we study have correlation coefficients between Q3 and Q4 anomaly signal rankings that are at least 0.75. These high correlations support a simple, but important insight – that the constituents of anomaly portfolios should be highly persistent.

We present evidence for this insight by examining the persistence of portfolio assignments. Table IV shows the percent of stocks in a given portfolio as of ($Q4_t$) that were in the same portfolio in prior periods (one quarter earlier ($Q3_t$), two quarters earlier ($Q2_t$), and one year earlier ($Q4_{t-1}$). We find that 66% of the stocks in the Average anomaly portfolio as of Q4 were also in the portfolio at Q3. In other words, two-thirds of the annual Average anomaly portfolio persists from Q3. That figure drops to 56% when considering stocks that remained in the anomaly portfolios from Q2 to Q4, and further to 32% for stocks remaining in the Average anomaly portfolio from last year. Table IV also shows that some anomalies (e.g., Asset Turnover (At) and Profitability (Pro)) are highly persistent while others (e.g., Earnings Surprise (Es) and Revenue Surprise (Rs)) are not.

[Table 4 about here.]

C. Four Models to Predict Anomaly Signals and Anomaly Portfolios

Given the high persistence of anomalies documented above, it follows that anomaly signals and the constituents of anomaly portfolios should be predictable. We explore this idea using four different prediction models.

Autoregressive models: Two of these models are autoregressive models, in which the current value of an anomaly signal is based on its preceding values, plus a stochastic term. These models represent the canonical random walk with drift. The first autoregressive model we test predicts the *level* of the anomaly signal given year-to-date information on that particular signal. This model is labeled the "AR Signals" model. The second autoregressive model predicts the *relative ranking* of anomaly signals using year-to-date information on the anomaly ranking (anomaly signals are ranked into deciles). We label this model "AR Rankings." Both models are of the form:

$$x_{4,t} = \delta + \phi_1 x_{3,t} + \phi_2 x_{4,t-1} + w_{4,t}, \tag{1}$$

where $x_{4,t}$ is either the anomaly signal or the anomaly ranking at Q4; $x_{3,t}$ is the signal or ranking one quarter earlier at Q3; and $x_{4,t-1}$ is the signal or ranking four quarters earlier, or last year's Q4. The parameter of interest, ϕ_1, measures the persistence in the autoregressive process, indicating the degree to which the anomaly signals or rankings at Q3 influences the Q4 value. The random error term is denoted as w.

It is important to note that we use a rolling-window strategy with all of our prediction models to prevent a look-ahead bias. Specifically, we use data up to year t to train the autoregressive models and then make a prediction about year $t + 1$. Then, using the predictions, we classify whether a stock will be in the long or short (or neither) leg of the anomaly portfolio at Q4.

Machine Learning model: We also study a machine learning model that uses past anomaly signals, anomaly rankings, and other firm-specific characteristics to predict whether a stock will be in the long or short leg of a given annual anomaly portfolio. The features considered in the model include the following: anomaly rank at Q3, anomaly rank at Q2, the interaction between the anomaly ranks at Q2 and Q3, the squares of the anomaly ranks at Q3 and Q2, the log of total assets, the interaction between the anomaly rank at Q3 and the log of total assets, the difference between the anomaly rank at Q3 and Q2, and the industry of the firm. Also, to prevent look-ahead bias, we train the model using data up to year t and then make predictions for year $t+1$.

The specific machine learning algorithm we use is a high-performance gradient-boosting machine called the LightGBM Classifier. Similar to other gradient-boosting machines, it is a tree-based algorithm that iteratively builds models while minimizing a loss function. LightGBM is ideal for our tests as it is tailored for classification tasks (such as classifying a stock as in or out of an anomaly portfolio) and efficiently handles large datasets.[18] Finally, it should be noted that we tested a similar machine learning algorithm, XGBoost, which made nearly identical predictions but with less efficiency.[19]

Martingale model: Finally, motivated by the high persistence of anomaly portfolios from Q3 to Q4, we use a martingale model that simply assumes that the annual anomaly portfolio ranking will be the same as the ranking as of Q3. That is, the conditional expected value of the anomaly signal ranking at Q4 is best approximated with the Q3 ranking. It is effectively a "random walk without drift," as the expectation of the error term is assumed to be zero. This model is of the form:

$$E[x_{4,t}|x_{3,t}] = x_{3,t}. \tag{2}$$

[18]Our sample can get quite large when we are making predictions for several thousands of stocks over 30 years for 28 different anomalies.

[19]We left all hyper-parameters of LightGBM at their default levels except for class weights, which gave a weight of 1 to stocks not inside the legs of anomaly portfolios and a weight of 2 to the stocks inside the legs of anomaly portfolios.

To assess the quality of each of these four prediction models, we examine their F1 Scores. The F1 Score measures a model's accuracy while considering both the precision and recall of the predictions, providing a single metric for the model's accuracy.[20] The F1 Score ranges between 0 and 1, with higher values indicating a higher degree of precision and recall, and thus a better prediction model.[21]

Table V shows the differences in model quality (F1 Scores) for each of the four prediction models and for all anomalies. For the Average anomaly, the Martingale model and ML model lead out, with F1 scores of 0.72. The differences in model quality are especially clear in Figure 2, which shows that the martingale model performs relatively well. Indeed, this most simple model is better than the two autoregressive models and equals the performance of the sophisticated machine learning model. While there is variation across anomalies, for almost all of them the martingale model has F1 Scores that are relatively better and nearly identical to those of the machine learning model. This suggests that even with a sophisticated algorithm and considering other inputs, the machine learning model nonetheless relies heavily on the anomaly rankings in Q3 to predict the ranking in Q4. In other words, the best model may be the simple martingale model.[22]

[Table 5 about here.]

[Figure 2 about here.]

This models' comparative performance can also be seen in Table VI and Figure 3 where the precision (Type 1 error rate) and recall (Type 2 error rate) are plotted. As was the case when comparing F1 Scores, the martingale and machine learning models dominate the

[20]Precision is the proportion of true positive predictions among all positive predictions. Recall is the proportion of true positive predictions among all actual positive cases.

[21]See Section A of the Internet Appendix for a formal discussion of prediction quality measures.

[22]While the machine learning and martingale models are highly accurate, on average, they do perform poorly for three anomalies: Earnings Surprise, Revenue Surprise, and the Tax anomaly. However, this is not surprising since two of these three anomalies are, by definition, constructed to be "surprises" and the third, taxes, is known to vary significantly from year to year while being less informative on a year-to-date basis.

autoregressive models. And again, the martingale and machine learning models are very similar.

[Figure 3 about here.]

[Table 6 about here.]

Finally, we also explore whether the quality of these models, or the predictability of the anomalies, has changed over time. As shown in Figure 4 the quality of the martingale has been relatively constant over time. In other words, it consistently perform well at forecasting future anomaly signals and the constituents of anomaly portfolios throughout our sample period.[23]

[Figure 4 about here.]

Overall, the results in this section show that anomaly signals are highly predictable. The finding that simplest prediction model, the martingale model, is the most effective at predicting annual anomaly portfolios is surprising. Even the sophisticated machine learning model cannot regularly beat the martingale model. Taken together, our results thus far suggest that the returns to trading early with perfect foresight may be achievable by investors. We investigate this idea in the next section.

D. Trading on Predicted Anomaly Signals

Can investors use the simple but powerful martingale model to trade before annual anomaly signals are released and earn high returns? In other words, can the high returns to perfect foresight be captured using the martingale model? In short, we find that the answer is "yes."

Figure 5 shows returns to the Average anomaly portfolio before and after the annual information release date. The return to the perfect foresight model is shown again (as in

[23]The results in Figure A1 of the Internet Appendix show a similar result for the Machine Learning model.

Figure 1), but now the return to the Average anomaly portfolio *predicted by the martingale model* is also shown.[24]

Two facts are immediately clear. First, trading using the martingale model is profitable. As detailed in Table VII, trading three months early using the martingale model yields 70 basis points (2.80% on an annualized basis). Further, a strategy that forms portfolios three months early using the martingale model then rebalances after the annual information release date could earn 248 basis points (5.02% annualized) in the six-month window around the release date.[25]

[Figure 5 about here.]

[Table 7 about here.]

The second fact: though positive and significant, the return to trading early using the martingale model is less than half of the return possible with perfect foresight. This is perhaps surprising, especially given that anomalies are highly persistent and predictable.[26]

D.1. Errors in Anomaly Prediction

To investigate this, we decompose the return earned by the martingale model based on whether the prediction was correct or incorrect. We further decompose incorrect predictions by the type of error. Specifically, we examine event-time return patterns for each of the following scenarios:

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[24]Figure 5 and Table II are replicated using the machine learning model in addition to the martingale model. These results are shown in the Section D of the Internet Appendix. Given the similarities between the machine learning and martingale models with respect to performance, the main text typically addresses only the martingale model while placing results for the machine learning model in the appendix.

[25]The estimate of 248 basis points adds together the 70 basis points earned before the information release date and the 178 basis points earned afterward (see Table II).

[26]Figure 5 and Table II are replicated using the machine learning model in addition to the martingale model. These results are shown in the Section D of the Internet Appendix. Given the similarities between the machine learning and martingale models with respect to performance, the main text typically addresses only the martingale model while placing results for the machine learning model in the appendix.

- correct predictions – cases in which a stock is correctly assigned to a long or short leg of an anomaly portfolio;
- false positive predictions – cases in which the model incorrectly predicts that a stock should be included in a particular portfolio, but in reality, it should not be included;
- false negative predictions – cases in which the model incorrectly predicts that a stock should not be included in a particular portfolio, but in reality, it should be included.

Figure 6 shows the return profiles of portfolios of correct, false positive, and false negative predictions from the martingale model.[27] The figure makes it clear that incorrect predictions are very costly. This is why the return to trading early using the martingale model fails to achieve even half of the return earned using perfect foresight.

[Figure 6 about here.]

As shown in Table VIII (which adds detail to Figure 6), false positive predictions result in losses of up to 60 basis points (2.42% annualized) in the three months before annual information releases. Nearer the information release date, one week before for instance, false positives can lose up to 33 basis points (18.7% annualized). And this trend continues after the information release date. Overall, making incorrect predictions before annual information releases is very costly.

[Table 8 about here.]

The results with respect to false negative predictions are even more striking and showcase, again, the costs of incorrect predictions. False negatives earn very large returns, even up to 297 basis points (12.4% annualized), in the three months before annual information releases. And again, the returns are highly concentrated around the annual information releases. In just the one week before annual information releases these stocks earn 108 basis points (74.8%

[27] A similar figure including the machine learning model is provided in Section D of the Internet Appendix.

annualized). Given that these returns are “missed”, in a sense, the costs they impose on an investor using the martingale model are large.

Taken together, while correct predictions are profitable, even approaching the performance of the perfect foresight model as can be seen in Table VIII, earning negative returns due to false positives and missing out on the large returns from false negative predictions results in an achievable return that is much lower than the perfect foresight model. This is true even with the high-quality prediction models.

Importantly, it should also be noted that the false negatives earn exceptionally high returns in the week immediately before the information release date and have the largest returns on the information release date and in the days just after. This suggests that the high concentration of anomaly returns around information release dates (both before and after) is driven by *new* and *surprising* information.

D.2. Time Trends in Returns

Having shown predictable patterns in anomaly returns before annual information release dates, and that some of these returns can be earned using a simple prediction model, we next examine whether these predictable patterns have survived in recent years or whether they only existed in the earlier part of our sample. Our analysis is motivated by the findings in McLean and Pontiff (2016) indicating that anomaly returns are weaker after anomalies are discovered and published,[28] and by Bowles et al. (2024) showing that in recent years anomaly returns are smaller and more concentrated in the weeks after annual information releases. For this exercise we divide our sample in half to compare the early period (1990-2006) with the recent period (2007-2023) and perform the same analysis as in the prior section. Figure 7 shows our first result.

[Figure 7 about here.]

[28] See also Ivkovic and Zekhnini (2024).

In the early part of our sample (1990-2006) returns to trading early using the martingale model were very high, even approaching the returns of the perfect foresight model. As can be seen in the figure, and also in Table IX, using the martingale model and trading three months early generated 201 basis points for the Average anomaly. Combining the returns over those three months with the return to holding the actual annual anomaly portfolios for three months after the information release date would result in a total return of approximately 400 basis points over those six months. In other words, in the 1990s and early 2000s the strategy of trading early earned a very large return.

[Table 9 about here.]

Two things have changed in the recent period. First, the perfect foresight model is almost one-third of the size as in the early period. Thus, even with perfect foresight, returns before information release dates are smaller. Second, there is no return to trading early using the martingale model.[29] This can be seen as the relatively flat line before trading-day zero in the second panel of Figure 7. One interpretation of this is that the returns to trading early using a simple prediction model (or even a more sophisticated machine learning model) have been arbitraged away. Additional evidence for this interpretation can be see in Figure 8, which shows the returns to correct, false positive, and false negative predictions in the two different time periods (the results are also shown in Panel B of Table IX.)

[Figure 8 about here.]

In the early period, correct predictions earned very large returns in the weeks before information releases, up to 260 basis points over three months. False negative predictions did even better: 330 basis points over three months. Most interestingly, even false positive predictions yield returns of 58 basis points in this early period. All together, in the early period correct predictions were profitable and false positive predictions were not costly. It

[29] As shown in Section D of the Internet Appendix, the same holds true for the machine learning model as well.

was still the case, however, that missing returns from the false negative predictions was costly.

The returns are far different in the recent period as correct predictions earned low returns and, in fact, almost no return until the week before the annual information release date. This is evidence of these returns being arbitraged away in recent years. Also, making prediction errors became increasingly costly. False positives from the martingale model lost 138 basis points in the three months before information dates. Together, earning much less for correct predictions and losing much more for false positive predictions results in the zero returns to trading early in recent years.

Most striking from these results are those with regards to the false negatives. In recent years the false negative predictions still earn high returns: these errors from the martingale model earned 268 basis points in the three months before information dates. Focusing on just the one week before the information dates, the false negatives earn 124 basis points. (On an annualized basis, this is 90%!) It is also interesting that the return after information release dates is highest for these stocks. The evidence in Figure 8 suggests that in the two weeks around information release dates these stocks earn approximately 200 basis points (67% on an annualized basis). What does this mean?

For one, the market is more efficient in recent years. While there was a time when investors could use the simple martingale model to predict annual anomaly portfolios and earn high returns in the three months before annual information release dates, that time has passed. Those returns have been arbitraged away as signal processing costs have diminished and the publicity of anomalies has increased.[30]

Second, and perhaps more importantly, anomaly returns still exist in recent years, but they are increasingly related to the release of new information. Returns to anomalies are not only highly concentrated around information release dates, but they are also highly concentrated in the stocks where the information is actually *new*. Again, Figure 8 shows

[30] See McLean and Pontiff (2016) and Bowles et al. (2024).

that the false negative predictions earn approximately 200 basis points in the two weeks around information release dates. Correct predictions (e.g., stocks that are unsurprisingly in the annual anomaly portfolios) earn almost nothing in these same two weeks. This is perhaps the strongest evidence yet that anomaly returns are driven by the release of new information.[31]

The above results lead to our final analysis. Given that returns to using the prediction models to trade three months (one quarter) early have been arbitraged away in recent years, we test whether predictions could have been made, and whether returns could have been earned, by trading six months (two quarters) early. Figure 9 shows the returns to a strategy that uses the martingale model as of the second quarter (Q2) and trades six months before annual information release dates. The results suggest that even in recent years, investors could have earned a positive return with this strategy. Indeed, the returns to correct and false positive predictions are both positive in the period from six months before to three months before information releases. This suggests that while the returns to making predictions and trading three months early have been arbitraged away, investors can potentially move earlier in event time and earn returns by making predictions and trading six months ahead of time. These findings are consistent with Greenwood and Sammon (2022) who show that index addition and deletion premiums are moving earlier and earlier in event time as a result of competition.

[Figure 9 about here.]

IV. Conclusion

There is a large literature on asset pricing anomalies, yet by tradition, many papers form anomaly portfolios annually, on June 30th, to ensure that trading signals have been publicly

[31] In related analysis we investigate abnormal trading volume for these anomalies both before and after annual information release dates and during both the early and recent periods in our sample. The main result from this analysis is that there is much more trading volume on information release dates in recent years. A larger discussion of this analysis are included in Section E of the Internet Appendix.

available long enough to prevent a look-ahead bias (e.g., Fama and French (1992)). More recent studies have shown that this leads to the use of stale information, and they instead advocate for forming anomaly portfolios on information release dates (Bowles et al. (2024)) or around news events (e.g., Engelberg et al. (2018)). The economic motivation is intuitive: the returns to anomaly signals should begin to accrue as soon as anomaly signals are publicly revealed.

We examine a simple but important follow-up question: Can an investor earn anomaly returns before anomaly signals are even released? We first show that many anomaly signals are highly predictable. By examining various models, including a sophisticated machine learning algorithm and simple autoregressive models, we find that a straightforward martingale model often provides the best results. In other words, a significant portion of the stocks in the long and short legs of anomaly portfolios remain in the portfolios from quarter to quarter. Our results show that investors (and researchers) do not need to wait until information is released to form portfolios based on anomaly signals.

If anomaly signals are highly predictable ex ante, an investor who moves faster than others should be able to outperform the competition. Our evidence supports this idea. Specifically, we show robust evidence that trading on predictable anomalies is highly profitable if done before the information release date. The evidence suggests that returns begin to react to anomaly signals even before they are publicly released. On average, an investor who trades on predictable anomalies using the previous quarter's information generates an additional return of approximately 3% on an annualized basis.

Overall, our study brings a simple intuition – that anomaly signals are predictable – to a mature and well-developed asset pricing literature. An investor with an understanding of the predictability of anomaly signals can significantly outperform others by simply trading on predictable signals. Moreover, the investor does not need a highly complex forecasting model, as simple models are highly predictive of future anomaly signals.

The fact that anomaly signals are predictable adds additional challenges to the notion of market efficiency. It suggests that the market may incorporate information into prices more slowly than previously thought. Our results show that investors appear to under-react to the predictability of accounting data that is used in anomaly portfolio assignment. As a result, returns tend to predictably move in the direction of information that has yet to be released.

In sum, our findings challenge the traditional methods for defining and measuring asset pricing anomalies. The results are inconsistent with anomaly explanations related to data mining or risk and instead suggest that anomalies are related to information about anomaly signals. In other words, many anomalies are more anomalous than previously recognized.

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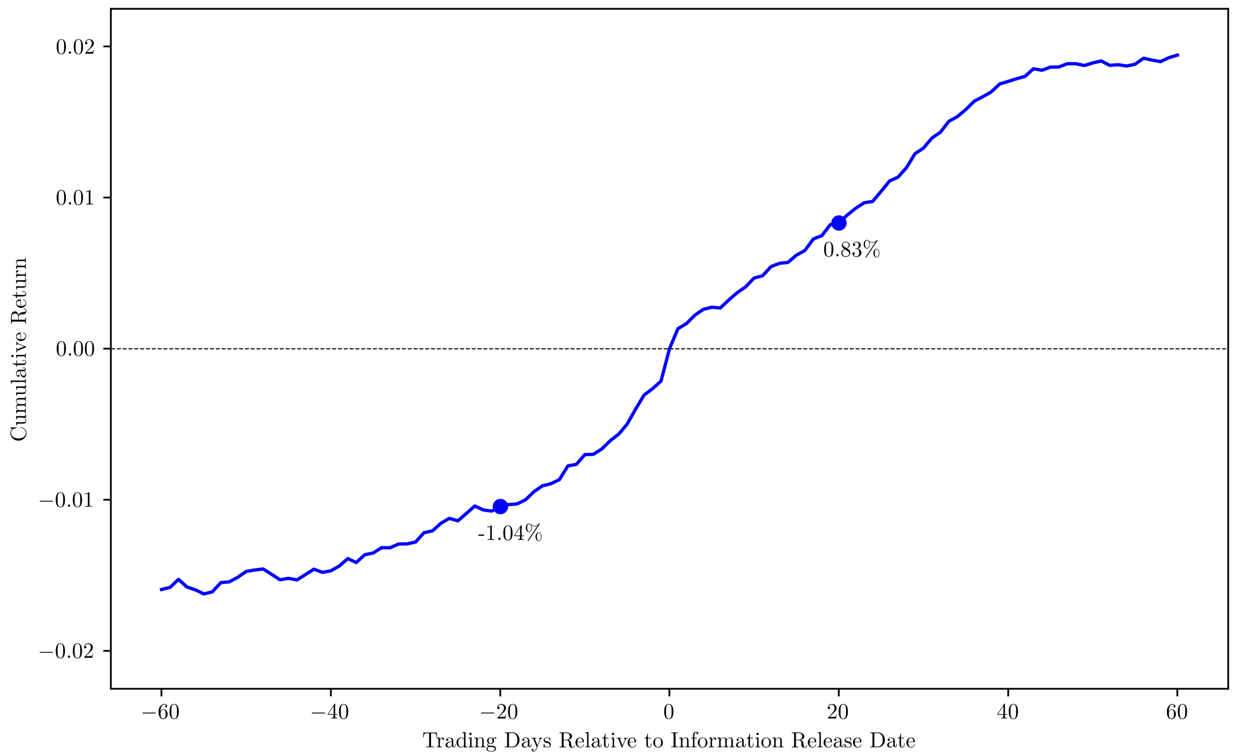


Figure 1. Anomaly Returns in Event Time

This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after annual information release dates. The returns have been scaled to be zero on the information release date. The compound returns, relative to the information release date, have been highlighted on the 20th trading day before and the 20th trading day after the information date.

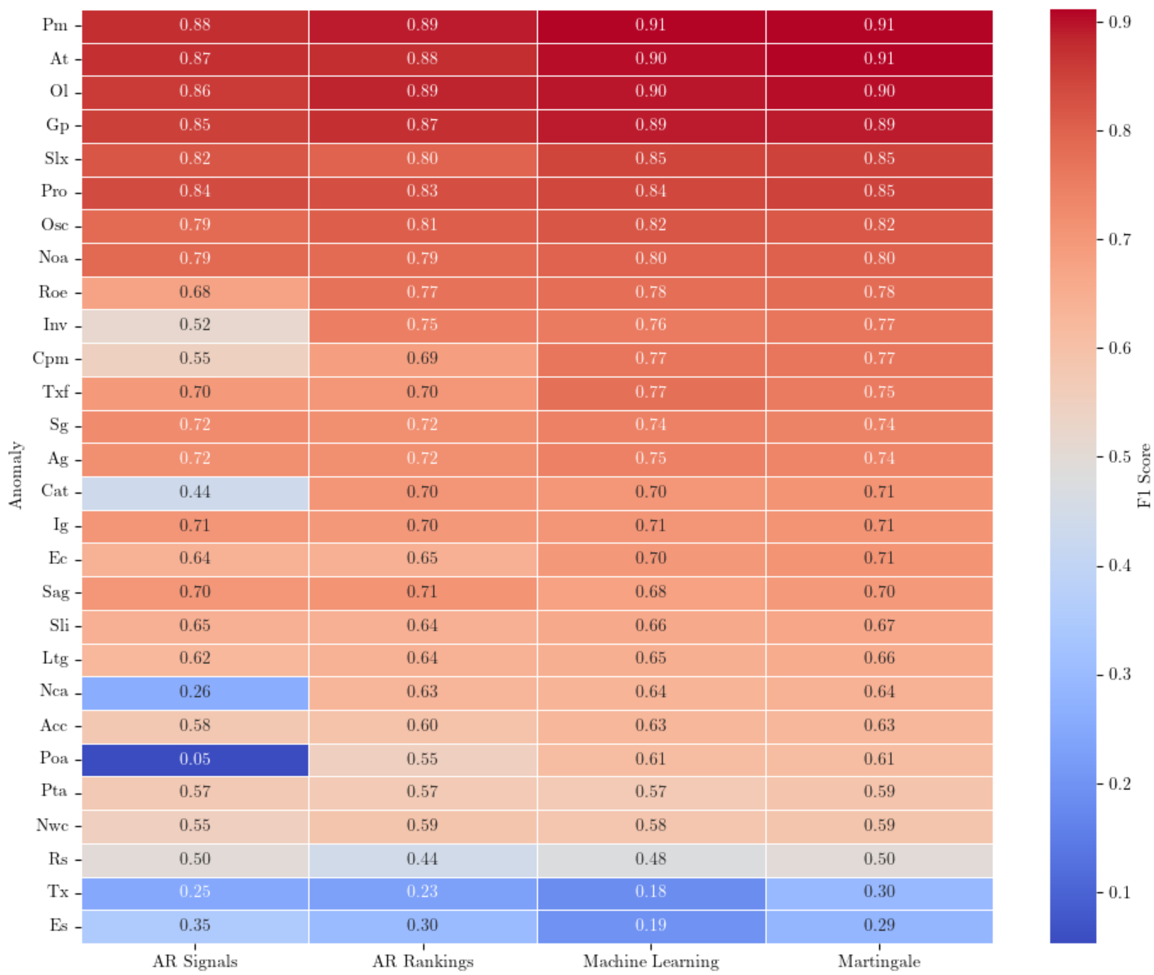


Figure 2. Heatmap of Model Quality - F1 Scores

The heatmap shows F1 Scores by anomaly and using four different prediction models: AR Signals, AR Rankings, Machine Learning, and the Martingale model. The F1 Score measures a model's accuracy while considering both the precision (the proportion of true positive predictions among all positive predictions) and recall (the proportion of true positive predictions among all actual positive cases) of the predictions, providing a single metric for the test's accuracy. A higher F1 Score indicates that a model for a given anomaly has a balance of high precision (few false positives) and high recall (few false negatives).

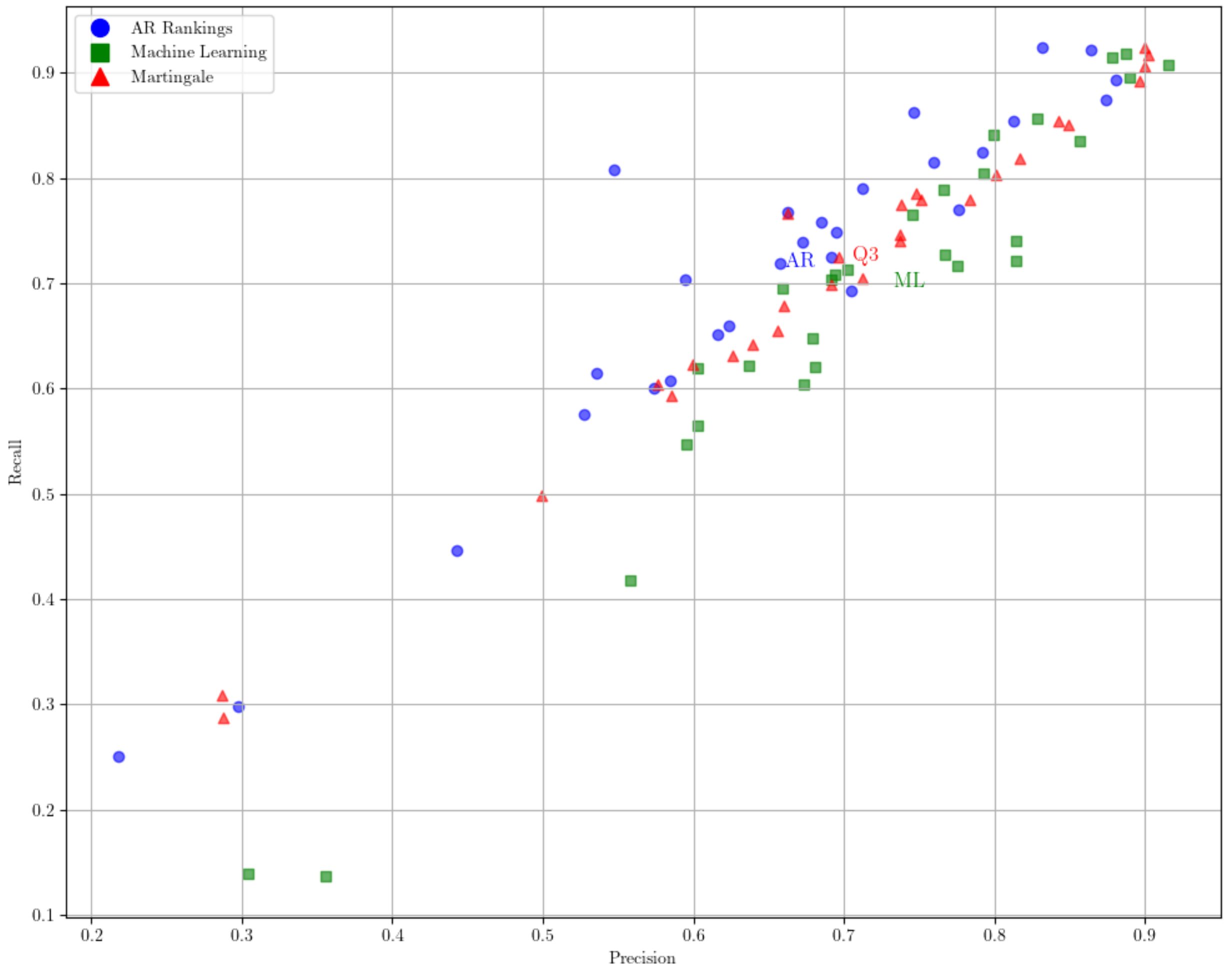


Figure 3. Scatter plot of Model Quality - Precision and Recall

The scatter plot shows the precision and recall scores for the 28 anomalies in our study and using three different prediction models: AR Rankings, Machine Learning, and the Martingale model. The point for the Average anomaly is shown with the model's abbreviation. Precision measures the proportion of true positive predictions among all positive predictions. Recall measures the proportion of true positive predictions among all actual positive cases.

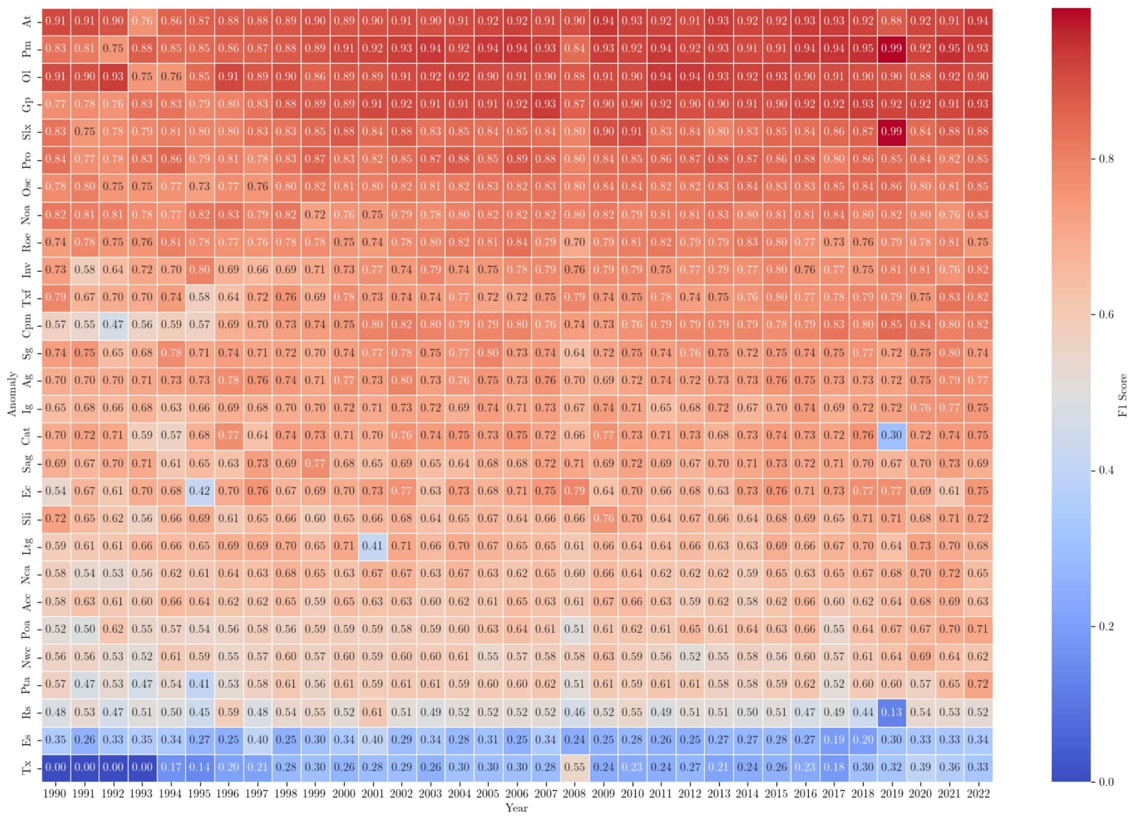


Figure 4. Heatmap of Martingale Model Quality by Year - F1 Scores

The heatmap shows F1 Scores by anomaly and by year using the Martingale model. The F1 Score measures a model's accuracy while considering both the precision (the proportion of true positive predictions among all positive predictions) and recall (the proportion of true positive predictions among all actual positive cases) of the predictions, providing a single metric for the test's accuracy. A higher F1 Score indicates that a model for a given anomaly and year has a balance of high precision (few false positives) and high recall (few false negatives).

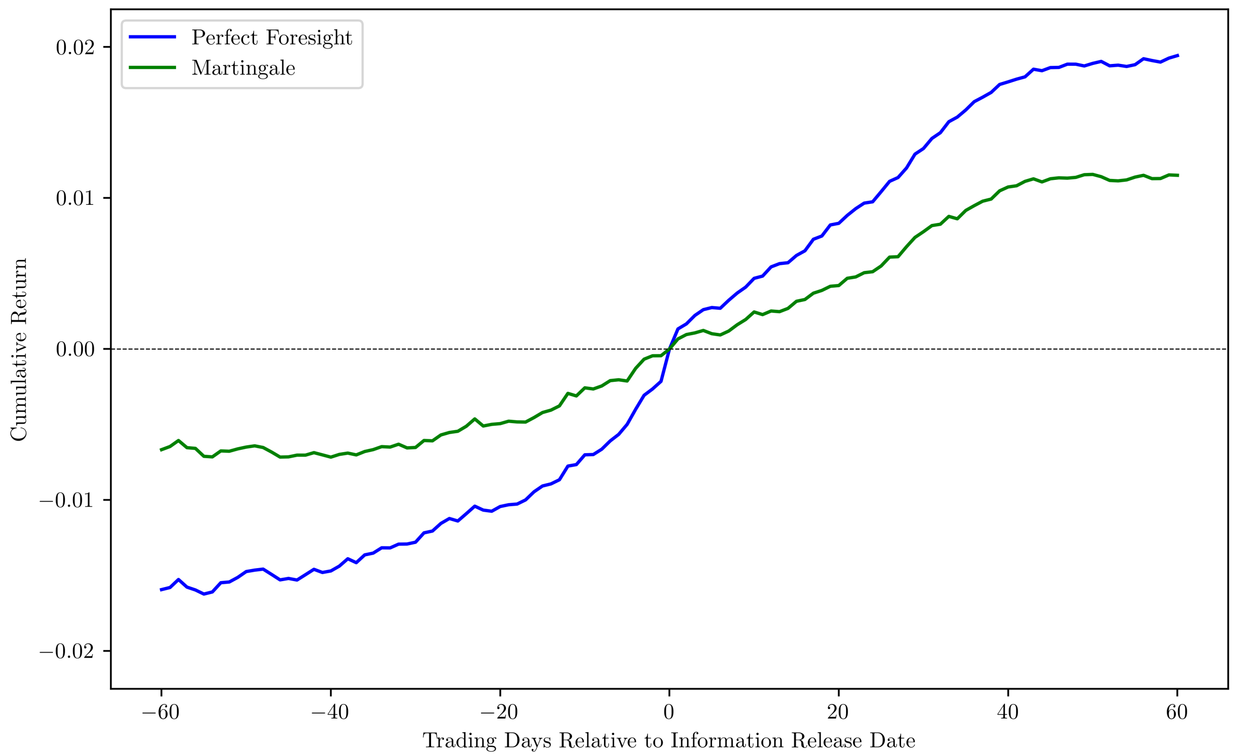


Figure 5. Anomaly Returns with the Martingale Predictions
This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after the information release dates. The blue line shows the return for the Perfect Foresight model. The green line shows the return for the Martingale model. The returns have been scaled to be zero on the information release date.

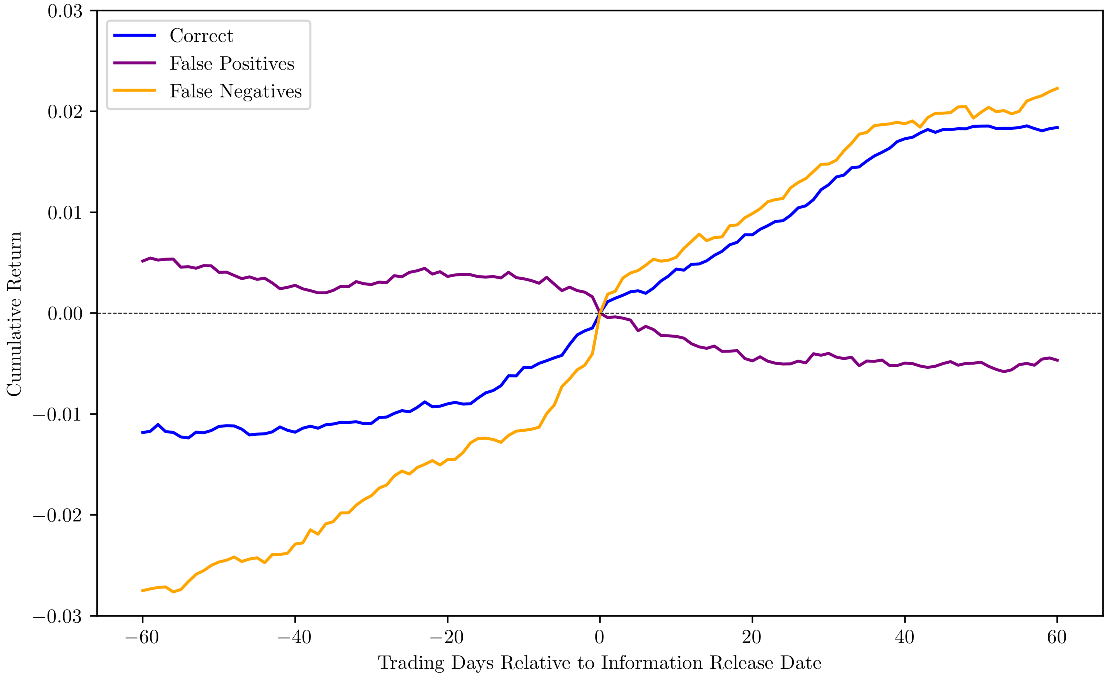
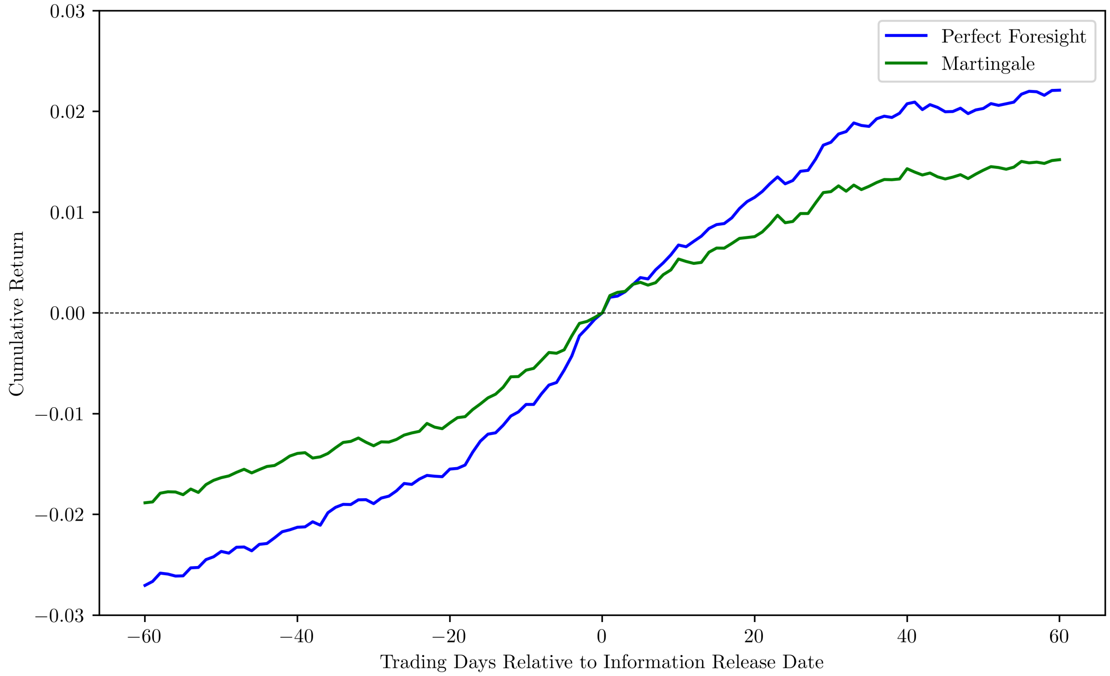
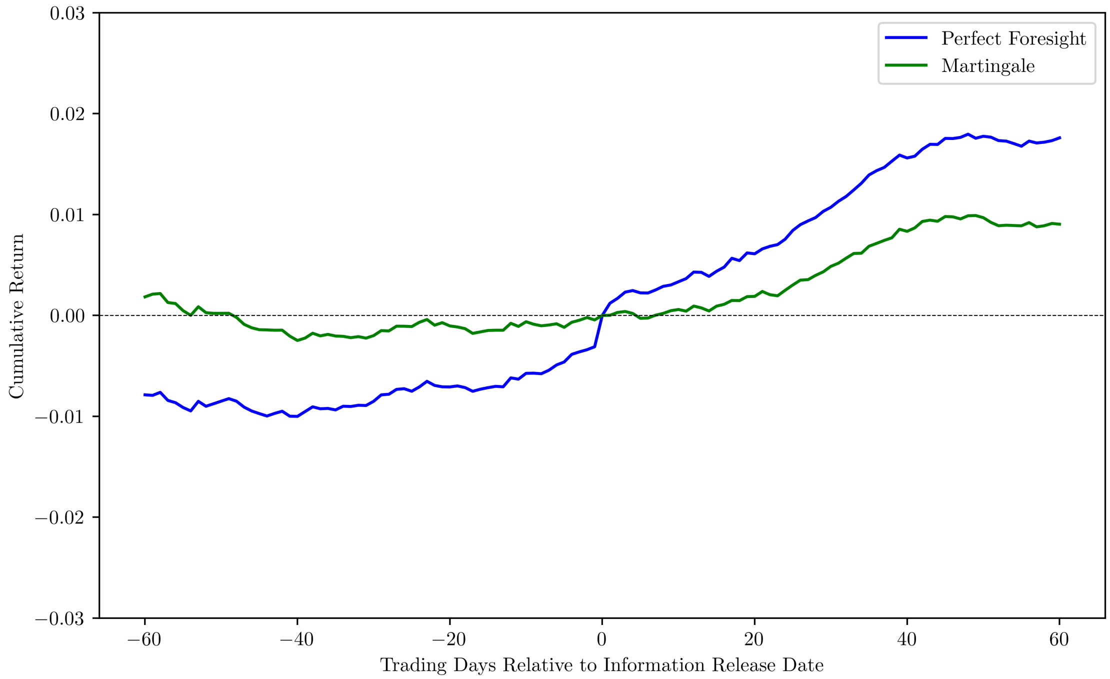


Figure 6. Anomaly Returns for Prediction Outcomes

This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after the information release dates and according to the prediction outcomes from the Martingale model. The blue line shows the return for the correct predictions. The purple line shows the return for false positive predictions. The yellow line shows the return for the false negative predictions. The returns have been scaled to be zero on the information release date.



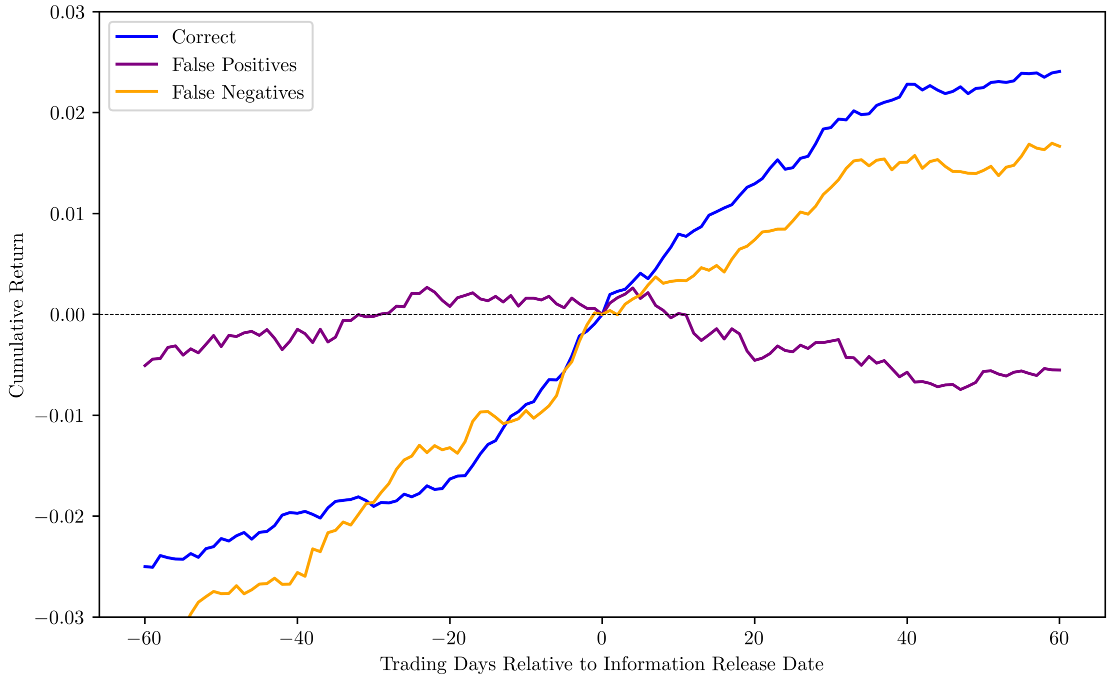
(a) Early Sample Period (1990-2006)



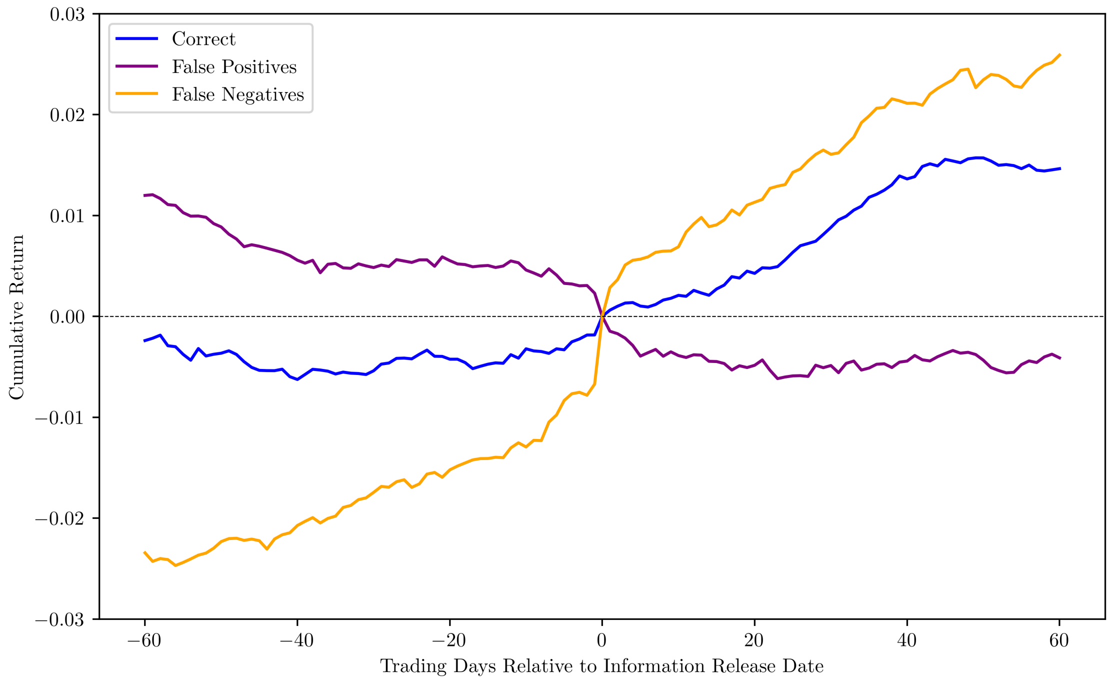
(b) Recent Sample Period (2007-2023)

Figure 7. Anomaly Returns with the Martingale Predictions - Time Trends

This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after the information release dates and according to the time period. The top panel shows returns over the early part of the sample period (1990-2006) while the bottom panel shows returns over the recent part of our sample (2006-2023). The blue line shows the return for the Perfect Foresight model. The green line shows the return for the Martingale model. The returns have been scaled to be zero on the information release date.



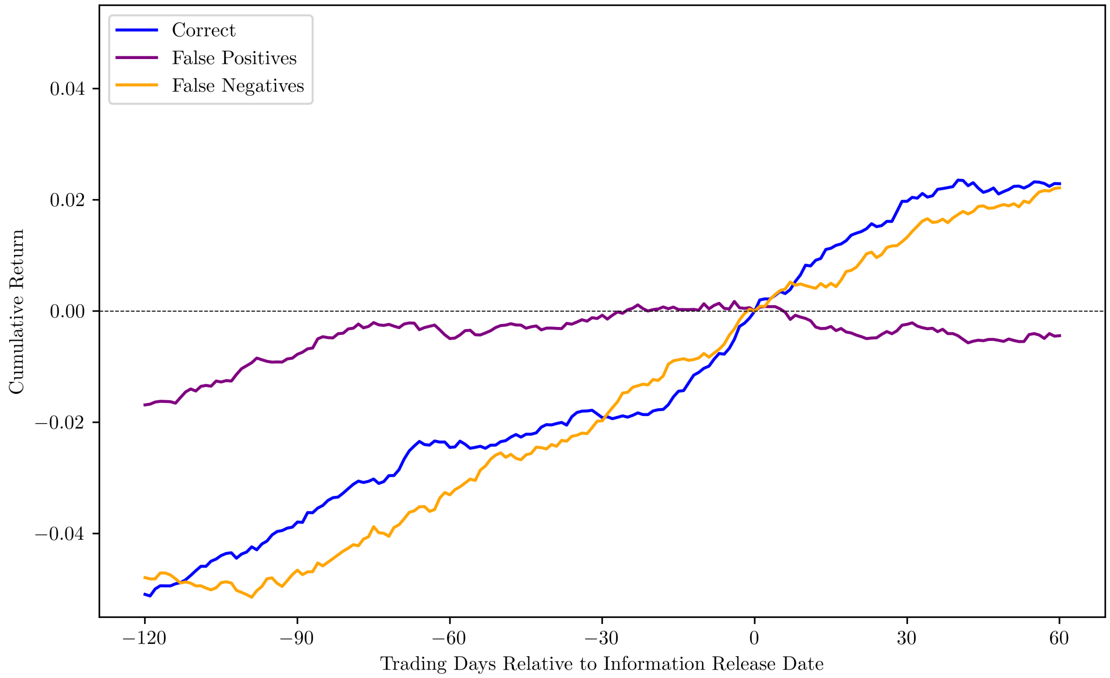
(a) Early Sample Period (1990-2006)



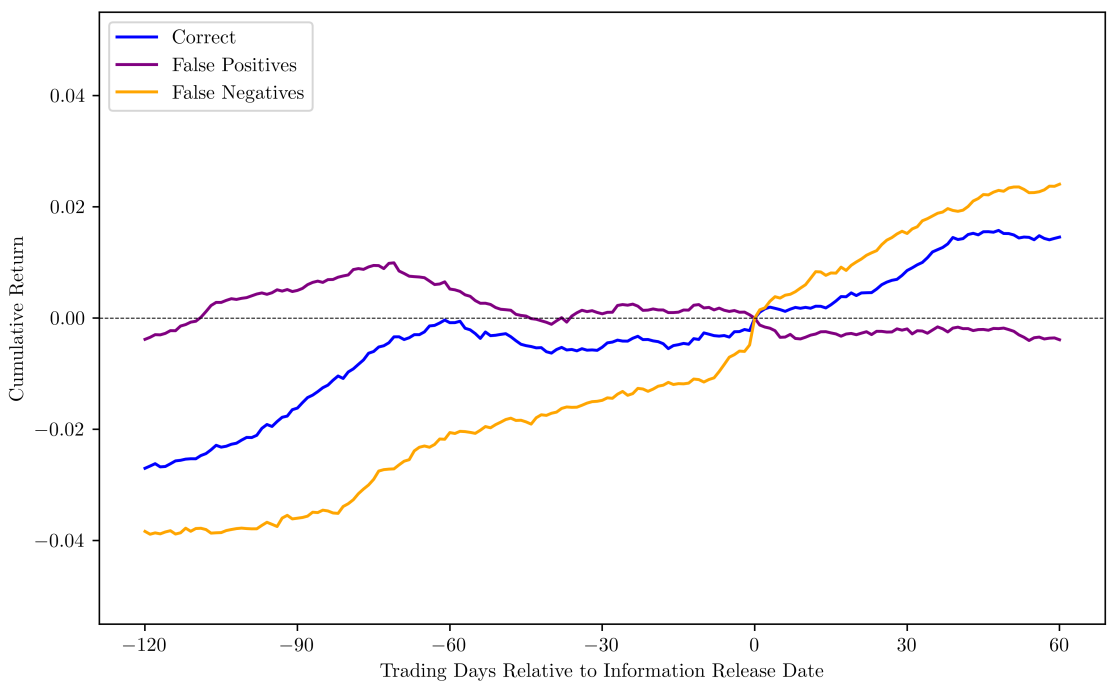
(b) Recent Sample Period (2007-2023)

Figure 8. Anomaly Returns for Prediction Outcomes - Time Trends

This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after the annual information release dates and according to the prediction outcomes from the Martingale model and according to the time period. The top panel shows returns over the early part of the sample period (1990-2006) while the bottom panel shows returns over the recent part of our sample (2007-2023). The blue line shows the return for the correct predictions. The purple line shows the return for false positive predictions. The yellow line shows the return for the false negative predictions. The returns have been scaled to be zero on the information release date.



(a) Early Sample Period (1990-2006)



(b) Recent Sample Period (2007-2023)

Figure 9. Anomaly Returns for Prediction Outcomes at Q2 - Time Trends
This figure shows the compound anomaly returns to the Average anomaly in the 120 trading days (six months) before and 60 trading days after annual information release dates and according to the prediction outcomes for the Martingale model at Q2 and according to the time period. The top panel shows returns over the early part of the sample period (1990-2006) while the bottom panel shows returns over the recent part of our sample (2007-2023). The blue line shows the return for the correct predictions. The purple line shows the return for false positive predictions. The yellow line shows the return for the false negative predictions. The returns have been scaled to be zero on the information release date.

Table I.
Summary Statistics

The table provides summary statistics for our sample which runs from 1990 through 2023. Panel A provides summary statistics for daily returns and total assets (in millions of USD) for all stocks in our sample. Panel B provides summary statistics for each of the anomaly variables.

(1)	(2)	(3)	(4)	(5)
Panel A. Daily Returns and Total Assets				
	Mean	Std. Dev.	Median	N
Daily Raw Returns	8 bps	508 bps	0 bps	112,254,604
Assets	$7,915	$63,698	$477	2,091,805
Panel B. Anomaly Characteristics				
Anomaly (abbreviation)	Mean	Std. Dev.	Median	N
Accruals (Acc)	-0.04	0.09	-0.04	70,672
Asset Growth (Ag)	0.14	0.42	0.06	89,681
Asset Turnover (At)	2.17	3.10	1.34	85,117
Change In Asset Turnover (Cat)	0.00	1.21	0.00	73,479
Change In Profit Margin (Cpm)	0.01	1.03	0.00	87,341
Earnings Consistency (Ec)	0.04	0.77	0.07	43,667
Earnings Surprise (Es)	-0.39	3.18	-0.05	64,078
Gross Profitability (Gp)	0.21	0.29	0.18	103,622
Inventory Growth (Ig)	0.01	0.04	0.00	88,261
Investments (Inv)	1.03	0.80	0.89	54,644
Growth In LT Net Operat. Assets (Ltg)	0.05	0.16	0.04	74,790
Non-Current Operating Assets (Nca)	0.00	0.12	0.00	89,697
Net Operating Assets (Noa)	0.52	0.39	0.54	83,702
Net Working Capital (Nwc)	0.00	0.08	0.00	70,666
Operating Leverage (Ol)	0.76	0.73	0.58	103,626
O-Score (Osc)	-0.52	3.36	-1.01	68,007
Profit Margin (Pm)	-0.15	3.36	0.35	100,963
Percent Operating Accruals (Poa)	-1.97	6.13	-0.66	94,524
Profitability (Pro)	-0.05	0.29	0.02	89,666
Percent Operating Accruals (Pta)	0.75	6.21	0.27	85,690
Return On Equity (Roe)	-0.06	0.85	0.07	103,606
Revenue Surprise (Rs)	-0.36	3.78	0.15	60,110
Sales Growth (Sag)	1,124	483	1,083	47,753
Sustainable Growth (Sg)	0.17	0.62	0.07	84,947
Sales Growth Less Invest. Growth (Sli)	-0.06	1.03	0.03	53,740
Sales Growth Less Exp. Growth (Slx)	0.02	0.47	0.00	60,104
Taxes (Tx)	0.95	1.27	0.99	72,233
Total External Finance (Txf)	0.07	0.24	0.00	83,374

Table II. Event Time Returns and Perfect Foresight

The table shows the event time anomaly returns to the Average anomaly over various time horizons relative to annual information release dates. The first row shows the abnormal return over the first three months (60 trading days) after the information release date. The next rows show the additional return from trading before the information release date. The returns are presented as compound returns in basis points, basis points per day, and annualized return in percent.

(1)	(2)	(3)	(4)
	Compound Return (bps)	Basis Points Per Day	Annualized Return (%)
Return from trading ***after*** the information release date and holding for 3 months.	178	3.1	7.7
Additional return for trading ***before*** the information release date:	Compound Return (bps)	Basis Points Per Day	Annualized Return (%)
1 trading day before	39	19.6	49.4
3 trading days before	53	13.2	33.2
1 week before	69	11.5	29.0
2 weeks before	89	8.1	20.4
1 month before	120	5.7	14.4
2 months before	161	3.9	9.9
3 months before	171	2.8	7.1

Table III. Serial Correlation of Anomaly Signlas

The table shows pairwise correlations between year end information ($Q4_t$) with the information from previous quarters (e.g., $Q3_t$, $Q2_t$, and $Q4t-1$). Correlations are reported separately for anomaly signals and anomaly rankings (into ten deciles). The row for the *Avgerage* measures the average correlation across all 28 anomalies.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Correlations with $Q4_t$					
	Signals			Rankings (1-10)		
Anomaly	$Q3_t$	$Q2_t$	$Q4_{t-1}$	$Q3_t$	$Q2_t$	$Q4_{t-1}$
Average	.41	.31	.05	.81	.71	.37
Accruals	.59	.60	-.48	.75	.62	.22
Asset Growth	.94	.99	.01	.84	.69	.26
Asset Turnover	.11	.02	.07	.97	.96	.92
Chg in Asset Turnover	.18	.01	-.62	.77	.67	.12
Chg in Profit Margin	.53	.48	-.64	.82	.70	-.03
Earnings Consistency	.38	.23	.81	.83	.73	.63
Earnings Surprise	.16	.10	-.07	.46	.30	-.37
Gross Profitability	.45	.19	.04	.97	.95	.88
Inventory Growth	.80	.14	.07	.70	.56	.10
Investments	.15	.18	.01	.88	.77	.31
Growth in LT Net Operating Assets	.77	.48	.28	.74	.60	.06
Non-current Operating Assets	.06	.11	.29	.70	.54	-.08
Net Operating Assets	.08	.11	.00	.94	.90	.82
Net Working Capital	.70	.71	-.50	.65	.51	-.16
Operating Leverage	.34	.22	.12	.97	.96	.91
O-Score	.29	.18	.22	.93	.87	.80
Profit Margin	.67	.60	.29	.97	.95	.88
Percent Operating Accruals	-.00	-.00	-.00	.77	.63	.40
Profitability	.56	.38	.17	.93	.88	.72
Percent Total Accruals	.00	.00	-.00	.71	.57	.08
Return on Equity	.00	.00	.00	.87	.79	.59
Revenue Surprise	.23	.03	-.00	.67	.43	-.23
Sales Growth	.90	.87	.85	.84	.79	.76
Sustainable Growth	.78	.21	-.00	.84	.71	.24
Sales Growth Less Inventory Growth	.29	.24	-.00	.75	.60	.23
Sales Growth Less Expenses Growth	.99	.96	-.07	.91	.83	.33
Tax	.00	.01	-.00	.56	.53	.57
Total External Financing	.65	.59	.58	.86	.73	.41

Table IV. Persistence of Anomaly Portfolios

The table shows the percent of stocks in the anomaly portfolio as of the release of year end information ($Q4_t$) that remained the same as of previous information releases. For example, 63% of the Accruals anomaly portfolio at $Q4_t$ remained unchanged from the $Q3_t$ information release. The row for *Average* measures the average percentages across all 28 anomalies.

(1)	(2)	(3)	(4)
	Pct. of Q4 Portfolio from Prior Quarter		
	$Q3_t$	$Q2_t$	$Q4_{t-1}$
Anomaly	Remained	Remained	Remained
Average	66	56	32
Accruals	63	50	22
Asset Growth	72	59	23
Asset Turnover	85	82	60
Chg in Asset Turnover	67	59	26
Chg in Profit Margin	68	57	19
Earnings Consistency	57	43	42
Earnings Surprise	26	13	2
Gross Profitability	85	78	66
Inventory Growth	68	56	22
Investments	66	54	31
Growth in LT Net Operating Assets	65	52	12
Non-current Operating Assets	59	45	12
Net Operating Assets	77	74	59
Net Working Capital	57	45	11
Operating Leverage	84	78	63
O-Score	81	72	57
Profit Margin	87	81	64
Percent Operating Accruals	55	42	24
Profitability	78	68	52
Percent Total Accruals	51	38	14
Return on Equity	75	65	44
Revenue Surprise	49	24	4
Sales Growth	57	50	45
Sustainable Growth	69	56	21
Sales Growth Less Inventory Growth	67	54	26
Sales Growth Less Expenses Growth	86	77	31
Tax	35	30	25
Total External Financing	68	55	31

Table V. F1 Scores for Prediction Models

The table shows the F1 Scores by anomaly and using four different prediction models: AR Signals, AR Rankings, Machine Learning, and the Martingale model. The F1 Score measures a model's accuracy while considering both the precision (the proportion of true positive predictions among all positive predictions) and recall (the proportion of true positive predictions among all actual positive cases) of the predictions, providing a single metric for the test's accuracy. A higher F1 Score indicates that a model for a given anomaly has a balance of high precision (few false positives) and high recall (few false negatives). The row for *Avg* measures the average F1 Score across all 28 anomalies. Abbreviations are used for the anomaly names. The full names can be found in the Internet Appendix and in a previous table.

(1)	(2)	(3)	(4)	(5)
Anomaly	AR Signals	AR Rankings	Machine Learning	Martingale
Avg	.63	.69	.72	.72
Acc	.58	.60	.63	.63
Ag	.72	.72	.75	.74
At	.87	.88	.90	.91
Cat	.44	.70	.70	.71
Cpm	.55	.69	.77	.77
Ec	.64	.65	.70	.71
Es	.35	.30	.19	.29
Gp	.85	.87	.89	.89
Ig	.71	.70	.71	.71
Inv	.52	.75	.76	.77
Ltg	.62	.64	.65	.66
Nca	.26	.63	.64	.64
Noa	.79	.79	.80	.80
Nwc	.55	.59	.58	.59
Ol	.86	.89	.90	.90
Osc	.79	.81	.82	.82
Pm	.88	.89	.91	.91
Poa	.05	.55	.61	.61
Pro	.84	.83	.84	.85
Pta	.57	.57	.57	.59
Roe	.68	.77	.78	.78
Rs	.50	.44	.48	.50
Sag	.70	.71	.68	.70
Sg	.72	.72	.74	.74
Sli	.65	.64	.66	.67
Slx	.82	.80	.85	.85
Tx	.25	.23	.18	.30
Txf	.70	.70	.77	.75

Table VI. Precision and Recall for Prediction Models

The table shows the precision and recall scores for the Avg anomaly using three different prediction models: AR Rankings, Machine Learning, and the Martingale model. Precision measures the proportion of true positive predictions among all positive predictions. Recall measures the proportion of true positive predictions among all actual positive cases. The table also reports the number of predictions that are True Positives, False Positives, False Negatives, and True Negatives.

(1) Metric	(2) AR Rankings	(3) Machine Learning	(4) Martingale
Precision	67%	74%	71%
Recall	72%	70%	73%
True Positives	225,119	219,600	226,936
False Positives	110,578	75,669	90,727
False Negatives	87,684	93,203	85,867
True Negatives	2,958,761	2,993,670	2,978,612

Table VII. Event Time Returns and Prediction Models

The table shows the event time anomaly returns to the Average anomaly over various time horizons relative to annual information release dates and using both the Perfect Foresight Model and the Martingale Model. The rows show the additional return from trading before the information release date. The returns are presented as compound returns in basis points and basis points per day.

(1)	(2)	(3)	(4)	(5)
	Perfect Foresight		Martingale	
Additional return for trading ***before*** the info release date:	Compound Return (bps)	Basis Points per day	Compound Return (bps)	Basis Points per day
1 trading day before	39	19.6	11	5.5
3 trading days before	53	13.2	19	4.9
1 week before	69	11.5	27	4.5
2 weeks before	89	8.1	38	3.4
1 month before	120	5.7	57	2.7
2 months before	161	3.9	77	1.9
3 months before	171	2.8	70	1.2

Table VIII. Event Time Returns and Prediction Outcomes

The table shows the event time anomaly returns to the Average anomaly over various time horizons relative to annual information release dates and relative to the outcomes using the Perfect Foresight Model and the Martingale Model. The prediction outcomes are Correct, False Positives, and False Negatives. The column Correct records the return to anomaly that were correctly predicted to be in the anomaly portfolio at the annual information release date. The False Positives column records the return to anomaly that were predicted to be in the annual anomaly portfolio, but were not (Type 1 errors). The False Negatives column records the return to stocks that were not predicted to be in the annual portfolio but were (Type 2 errors). The rows show the additional return from trading before the information release date. The returns are presented as compound returns in basis points.

(1)	(2)	(3)	(4)	(5)
	Compound Return (bps)			
	Perfect Foresight	Martingale		
Additional return for trading ***before*** the info release date:		Correct	False Positives	False Negatives
1 trading day before	39	29	-25	69
3 trading days before	53	42	-30	82
1 week before	69	55	-33	108
2 weeks before	89	73	-40	134
1 month before	120	103	-46	167
2 months before	161	128	-30	256
3 months before	171	127	-60	297
Return 3 months ***after***	178	171	-43	198
N	147,943	108,726	42,601	39,217

Table IX. Event Time Returns and Prediction Models - Time Trends

The table shows the event time anomaly returns to the Average anomaly over various time horizons relative to annual information release dates and relative to the outcomes from various prediction models: the Perfect Foresight Model (PF), the Martingale Model (Q3), and a Machine Learning Model (ML). The sample is also divided into an early period (1990-2006) and a recent period (2007-2023). The prediction outcomes are Correct, False Positives, and False Negatives. The column Correct records the return to stocks that were correctly predicted to be in the anomaly portfolio at the annual information release date. The False Positives column records the return to anomaly that were predicted to be in the annual anomaly portfolio, but were not (Type 1 errors). The False Negatives column records the return to stocks that were not predicted to be in the annual portfolio but were (Type 2 errors). The rows show the additional return from trading before the info date. The returns are presented as compound returns in basis points.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Basis Points Before Info Dates by Prediction Model						
	Early Period (1990-2006)			Recent Period (2007-2023)		
	PF	Q3	ML	PF	Q3	ML
1 trading day before	30	25	29	46	2	4
1 week before	83	56	60	61	8	14
1 month before	176	131	137	83	7	12
3 months before	279	198	201	92	-19	-7
Panel B. Basis Points Before Info Dates by Prediction Outcomes (Martingale)						
	Early Period (1990-2006)			Recent Period (2007-2023)		
	Correct	False Positives	False Negatives	Correct	False Positives	False Negatives
1 trading day before	35	5	14	25	-46	105
1 week before	83	1	82	38	-56	124
1 month before	191	-3	135	46	-74	187
3 months before	260	58	330	30	-138	268

Internet Appendix for "Predicting Anomalies"

This internet appendix[1] provides additional empirical evidence to supplement the main text.

[1]Citation format: Bowles, Boone, Adam V. Reed, Matthew C. Ringgenberg, and Jacob R. Thornock, Internet Appendix to "Predicting Anomalies." Working Paper, 2025.

A. *Prediction Quality Measures*

We study the quality of the four different prediction models by analyzing each model's precision, recall, and F1 Score. The calculations for the three variables are detailed just below. As a description, the precision of a model measures the proportion of true positive predictions among all positive predictions. A high precision indicates few Type 1 errors. Recall measures the proportion of true positive predictions among all actual positive predictions. A high recall indicates few Type 2 errors. The F1 Score is the harmonic mean of precision and recall and provides a single measure that balances both Type 1 and Type 2 errors.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

B. Snapshot Details

Snapshot is a database within Compustat that provides fundamental information for firms and details when fundamental information was updated in the public record. From the Snapshot manual:[2]

> Compustat Snapshot North America ("Snapshot") is the premier historical analysis and backtesting database that provides fundamental financial data on publicly traded companies and shows all values obtained in the data collection process. The Snapshot database creates a historical investment environment by showing the information that was available at that time in history.
>
> Snapshot contains fundamental financial data from the reported annual and quarterly sources, retaining original values and all succeeding changes from the income statement, balance sheet, and cash flow statements. In addition, Snapshot provides both the preliminary data and final data with annual, quarterly and year-to-date periodicities known at user-specified observation dates. This information enables you to identify what item values have changed and when they changed.

Within Snapshot, perhaps the most salient variable is the *Effective Date*, which captures the date when a company's "fundamental data is captured from productions of the S&P Capital IQ's Compustat database." In other words, the effective date records that date that Compustat noticed that a new book assets or net income amount had been released to the public. Prior to December 2008, Compustat used weekly productions to record data. Beginning in 2008, Compustat uses intraday productions to record data changes.

Based on the Snapshot manual, the earliest effective date is December 14, 1986. This date applies to financial statements prior to 1986 as this was the date Compustat recorded the fundamental information. Obviously, information released in financial statements in 1976 or

[2]See Compustat Snapshot User Guide, July 24, 2023.

1984, for example, would have been public knowledge prior to December of 1986. However, the effective date is capturing *when* Compustat recorded the data, which, after 1986 took place weekly and after 2008 took place at least daily. As a result of this, we limit our sample to information releases beginning in 1990.

Finally, we utilize SAS code provided in the Snapshot manual to use the effective dates for fundamental information. In essence, we follow Snapshot's guidance to identify the date when information was updated via the release of new financial information.

C. Construction of Anomaly Variables

This appendix provides details regarding the anomalies included in the paper. Each anomaly is listed, along with the paper originally citing the anomaly, a description of how frequently the original paper rebalanced the anomaly portfolios, and details on anomaly construction.

Anomaly	Paper	Original Rebalancing	Our Calculation
Accruals (Acc)	Sloan (1996)	Firms are ranked into deciles based on accruals. Hedge returns for one year ahead are calculated beginning four months after the end of the fiscal year.	$ACC = \frac{WC_t - WCt-1}{\frac{1}{2}(A_t + A_{t-1})}$ WC = Working Capital A = Total Assets WC = current assets - cash and equivalents - current liabilities + debt in current liabilities + taxes payable - depreciation and amortization
Asset Growth (Ag)	Cooper et al. (2008)	Ranked into deciles at the end of June.	$AG = \frac{A_t - A_{t-1}}{A_{t-1}}$ A = Total Assets
Asset Turnover (At)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$AT = \frac{Sales_t}{\frac{1}{2}(NOA_t + NOA_{t-1})}$ NOA = Net Operating Assets
Change in Asset Turnover (Cat)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$CAT = AT_t - AT_{t-1}$ AT = Asset Turnover (defined previously)
Change in Profit Margin (Cpm)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$CPM = PM_t - PM_{t-1}$ PM = Profit Margin (defined below)
Earnings Consistency (Ec)	Alwathainani (2009)	Consistency is based on the number of years in the preceding five years that the firm has had high earnings (low earnings), defined as falling within the top (bottom) 30th percentile. Portfolio returns are calculated beginning on either January or April first.	$EC = \frac{1}{5}(EG_t + EG_{t-1} + EG_{t-2} + EG_{t-3} + EG_{t-4})$ $EG = \frac{EPS_t - EPS_{t-1}}{(\frac{1}{2})EPS_{t-1} + EPS_{t-2}}$ // If EPS_t is opposite sign of EPS_{t-1} then don't include.

Anomaly	Paper	Original Rebalancing	Our Calculation
Earnings Surprise (Es)	Foster et al. (1984)	Earnings surprises are ranked into deciles quarterly.	$ES = \frac{EPS_t - EPS_{t-1} - Drift}{SD}$ $Drift =$ mean quarterly EPS over the preceding seven quarters. SD is the standard deviation of the difference between the preceding seven EPS values and the drift.
Gross Profitability (GP)	Novy-Marx (2013)	Ranked into quintiles at the end of June.	$GP = \frac{Sales_t - COGS_t}{A_t}$
Inventory Growth (Ig)	Thomas and Zhang (2002)	Ranked into deciles annually. Return calculations begin four months following fiscal year-end.	$INV = \frac{Inv_t - Inv_{t-1}}{(A_t + A_{t-1})/2}$ $Inv =$ Inventory
Investments (Inv)	Titman et al. (2004)	Ranked into deciles annually. Return calculations begin four months following fiscal year-end.	$INV = \frac{CE_t}{(\frac{1}{3})(CE_{t-1} + CE_{t-2} + CE_{t-3})}$ $CE = \frac{CAPX}{Sales}$
Growth in Long Term Net Operating Assets (Ltg)	Fairfield et al. (2003)	Stocks are sorted into deciles based on growth in long-term net operating assets. Returns are calculated beginning in April after fiscal year-end.	$LTG = NOA_t - NOA_{t-1} - ACC_t$ $NOA =$ receivables + inventory + other current assets + PP&E +intangible assets + other assets - accounts payable - other current liabilities - other liabilities all scaled by total assets. ACC is defined previously.
Non-current Operating Assets (Nca)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$NCA = \frac{chgOA}{\frac{1}{2}(AT_t + AT_{t-1})}$ $OA = AT - ACT - IVAO - LT + DLC + DLTT$
Net Operating Assets (Noa)	Hirshleifer et al. (2004)	Stocks are sorted into deciles. Returns are calculated beginning 4 months after fiscal year-end	$NOA = \frac{OA_t - OL_t}{A_{t-1}}$ $OA_t = AT_t + CHE_t$ $OL_t = AT_t - DLTT_t - MIB_t - PSTK_t - CEQ_t$

Anomaly	Paper	Original Rebalancing	Our Calculation
Net Working Capital (Nwc)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$NWC = \frac{NWC_t - NWC_{t-1}}{\frac{1}{2}(A_t + A_{t-1})}$ $NWC_t = ACT_t - CHE_t - LCT_t + DLC_t$
Operating Leverage (Ol)	Novy-Marx (2010)	Ranked into quintiles at the end of June.	$OL = \frac{COGS_t + SG\&A_t}{A_t}$
O-Score (Osc)	Dichev (1998)	Ranked into deciles. Returns are calculated beginning six months after fiscal year-end.	$OSC = -1.32 - 0.407(ln(A)) + 6.03(\frac{L}{A}) - 1.43(\frac{CA-CL}{A}) + 0.076(\frac{CL}{CA}) - 1.72I(L > A) - 2.37(\frac{NI}{A}) - 1.83(\frac{IO}{L}) + 0.285I(NI_t + NI_{t-1} < 0) - 0.521(\frac{NI_t - NI_{t-1}}{\lvert NI_t + NI_{t-1}\rvert})$ A = total assets L = total liabilities CA = current assets CL = current liabilities NI = net income IO = income from operations $I()$ is the indicator operator taking the value of one if true and zero otherwise.
Profit Margin (Pm)	Soliman (2008)	Measures control variables from last fiscal year-end. Starts calculating monthly returns during the first month of the fiscal year.	$PM = \frac{Sales - COGS}{Sales}$
Percent Operating Accruals (Poa)	Hafzalla et al. (2011)	Returns are calculated beginning four months after the end of the fiscal year.	$POA = \frac{IB_t - OANCF_t}{\lvert IB_t\rvert}$ IB = Income before extraordinary items $OANCF$ = Net cash flow
Profitability (Pro)	Balakrishnan et al. (2010)	Measures profitability at date of earnings announcement and measures returns from earnings announcement date.	$PRO = \frac{Earnings_t}{Assets_{t-1}}$

Anomaly	Paper	Original Rebalancing	Our Calculation
Percent Total Accruals (Pta)	Hafzalla et al. (2011)	Returns are calculated beginning four months after the end of the fiscal year.	$PTA = NI + SSTKY - PRSTKCY - DVY - OANCFY - FINCFY - IVNCFY$ All scaled by absolute value of net income. NI = Income before extraordinary items $OANCFY$ = Net cash flow $SSTKY$ = Sale of common and preferred stock $PRSTKCY$ = Purchase of common and preferred stock DVY = Cash Dividends $FINCFY$ = Net cash from financing activities $IVNCFY$ = Net cash from investment activities
Return on Equity (Roe)	Haugen and Baker (1996)	"We assume a reporting lag of 3 months." We take this to mean they start 3 months after the fiscal year-end.	$ROE = \frac{NI_t}{BE_t}$ BE = Common Equity+Deferred Taxes NI = Net Income
Revenue Surprise (Rs)	Jegadeesh and Livnat (2006)	Revenue surprises are ranked into quintiles quarterly. Abnormal returns are measured from the earnings announcement date.	$RS = \frac{REV_t - REV_{t-1} - Drift}{SD}$ $Drift$ = mean quarterly REV over the preceding seven quarters. SD is the standard deviation of the difference between the preceding seven REV values and the drift.
Sales Growth (Sag)	Lakonishok et al. (1994)	Ranked into quintiles at the end of April.	$SAG = (5 \times R_t) + (4 \times R_{t-1}) + (3 \times R_{t-2}) + (2 \times R_{t-3}) + (1 \times R_{t-4})$ All scaled by 15. R = rank of sales growth as of earnings announcement.

Anomaly	Paper	Original Rebalancing	Our Calculation
Sustainable Growth (Sg)	Lockwood and Prombutr (2010)	Ranked into deciles or quintiles at the end of June.	$SG = \frac{BE_t}{BE_{t-1}}$
Sales Growth Less Inventory Growth (Sli)	Abarbanell and Bushee (1998)	Anomaly variable measured from annual financial statements for December 31st fiscal-year-end firms. Returns are measured from April 1st to March 31st of following year.	$SLI = SAG - IVG$ $SAG = \frac{REV_t - \frac{1}{2}(REV_{t-1}+REV_{t-2})}{\frac{1}{2}(REV_{t-1}+REV_{t-2})}$ $IVG = \frac{INV_t - \frac{1}{2}(INV_{t-1}+INV_{t-2})}{\frac{1}{2}(INV_{t-1}+INV_{t-2})}$ INV = inventory.
Sales Growth Less Expenses Growth (Slx)	Abarbanell and Bushee (1998)	Anomaly variable measured from annual financial statements for December 31st fiscal-year-end firms. Returns are measured from April 1st to March 31st of following year.	$SLX = SAG - XG$ $SAG = \frac{REV_t - \frac{1}{2}(REV_{t-1}+REV_{t-2})}{\frac{1}{2}(REV_{t-1}+REV_{t-2})}$ $XG = \frac{XSGA_t - \frac{1}{2}(XSGA_{t-1}+XSGA_{t-2})}{\frac{1}{2}(XSGA_{t-1}+XSGA_{t-2})}$ $XSGA$ = selling and administrative expenses.
Tax (Tx)	Lev and Nissim (2004)	Anomaly variable is updated annually at the beginning of May.	$TX_t = \frac{TXFO_t + TXFED_t}{0.35 \times IB_t}$
Total External Financing (Txf)	Bradshaw et al. (2006)	Returns are calculated beginning four months after the end of the fiscal year.	$TXF = SSTKY - PRSTKCY - DVY + DLTISY - DLTRY$ Scaled by average of the preceding two years of total assets. $SSTKY$ = Sale of common stock. $PRSTKCY$ = Purchase of common stock. DVY = cash dividends. $DLTISY$ = Long term debt issuance. $DLTRY$ = Long term debt reduction.

D. Results from Machine Learning Model

Several of the results described in the paper have been replicated while including results with respect to the Machine Learning model.

[Figure A1 about here.]

[Figure A2 about here.]

[Table AI about here.]

[Figure A3 about here.]

[Table AII about here.]

[Figure A4 about here.]

[Table AIII about here.]

[Figure A5 about here.]

E. Time Trends in Trading Volume

Given the findings with respect to returns, we also examine patterns in abnormal trading volume around annual information release dates. To do this we calculate daily abnormal trading volume as a stock's trading volume on a given day divided by the average daily volume over the 121-trading day period around information release dates. We then compute the average daily abnormal trading volume for the Average anomaly in event time and assuming perfect foresight. For instance, an abnormal volume measure of 0.20 indicates that volume on that day was 20% higher than the six-month average. As in the prior analysis, we divide our sample into early and recent periods to investigate potential shifts over time. Our findings are presented in Figure A6.

[Figure A6 about here.]

Figure A6 shows that trading activity has become more concentrated on information release dates in recent years. In this period, abnormal trading volume peaks at 0.80 on annual information release dates, indicating that volume is 80% higher than the average daily volume. By comparison, abnormal volume in the early period peaked at approximately 0.10. Together, these results indicate that information release dates have gained importance for both anomaly stocks and investors.[3]

Furthermore, in the early part of our sample abnormal volume remained relatively elevated (around 0.10) for the entire week leading up to annual information release dates. This is in contrast to the singular peak seen in recent years. Although this might initially appear to suggest front-running in the early years, it more likely reflects changes in information release timing. As demonstrated in Bowles et al. (2024), during the 1990s and early 2000s, earnings announcements often preceded 10-K filings by several weeks and typically lacked detailed financial statements. This sequence likely explains the elevated trading volume leading up to annual information releases. By contrast, in the late 2000s and 2010s, firms frequently issued

[3]This finding corroborates the results in Bowles et al. (2024).

detailed financial statements alongside earnings announcements, which were quickly followed by 10-K reports. Thus, in recent years, the earnings announcement date often functions as the primary information release date.

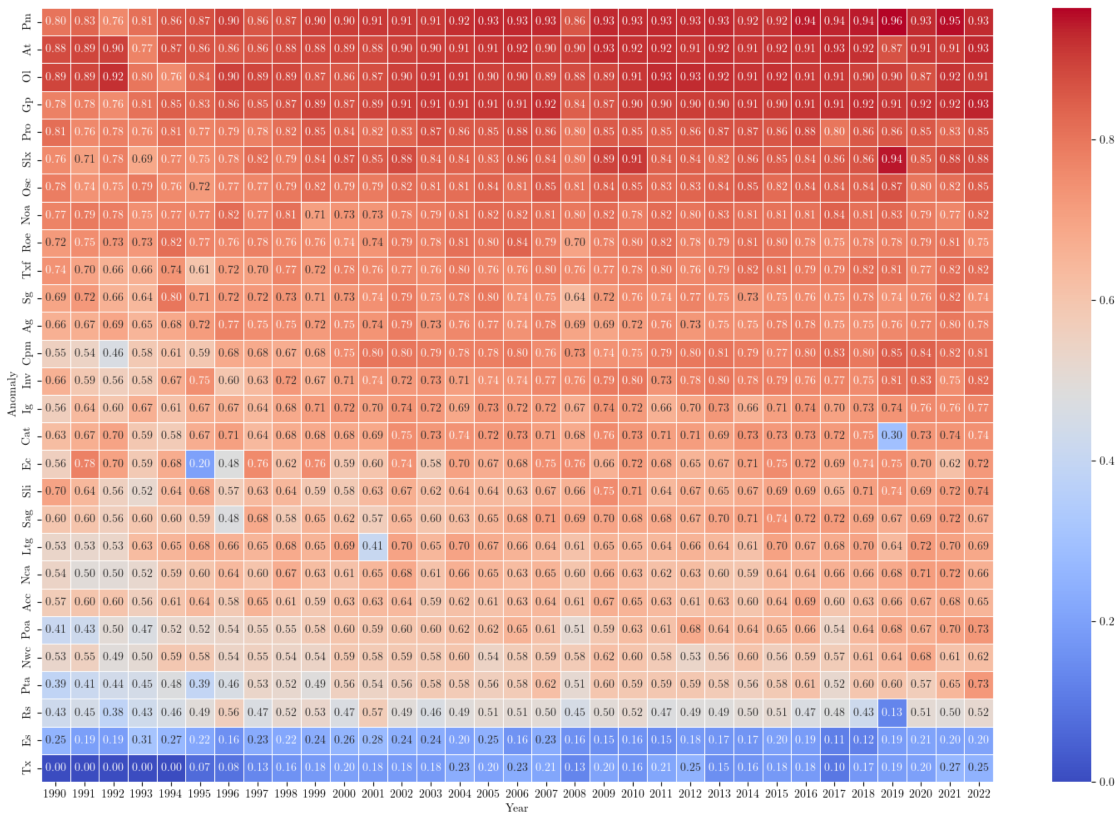


Figure A1. Heatmap of Machine Learning Model Quality by Year - F1 Scores
The heatmap shows F1 Scores by anomaly and by year using the Machine Learning model. The F1 Score measures a model's accuracy while considering both the precision (the proportion of true positive predictions among all positive predictions) and recall (the proportion of true positive predictions among all actual positive cases) of the predictions, providing a single metric for the test's accuracy. A higher F1 Score indicates that a model for a given anomaly and year has a balance of high precision (few false positives) and high recall (few false negatives).

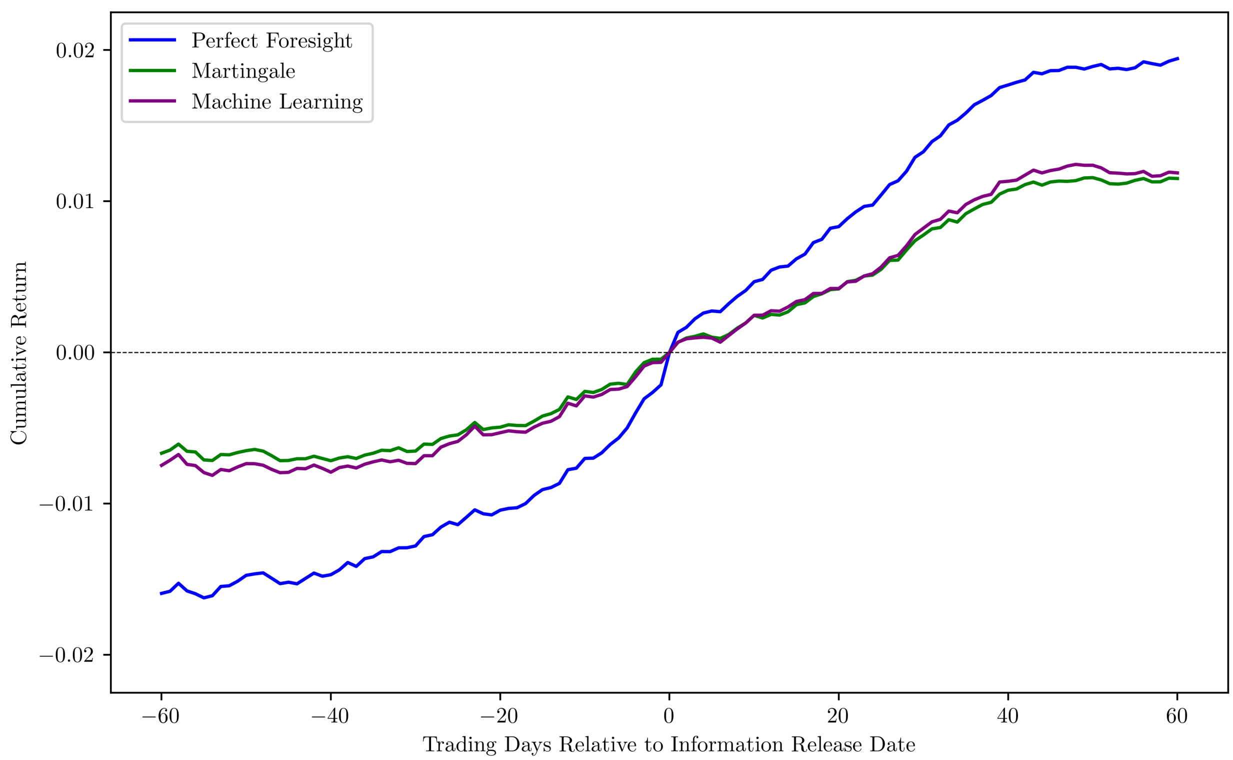
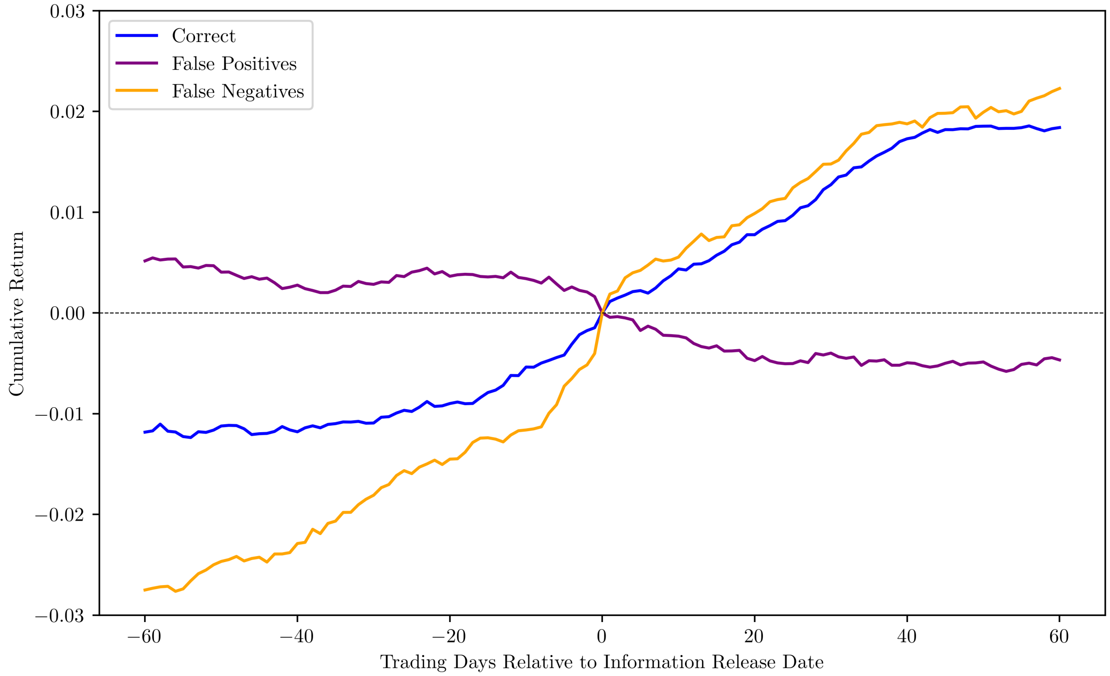
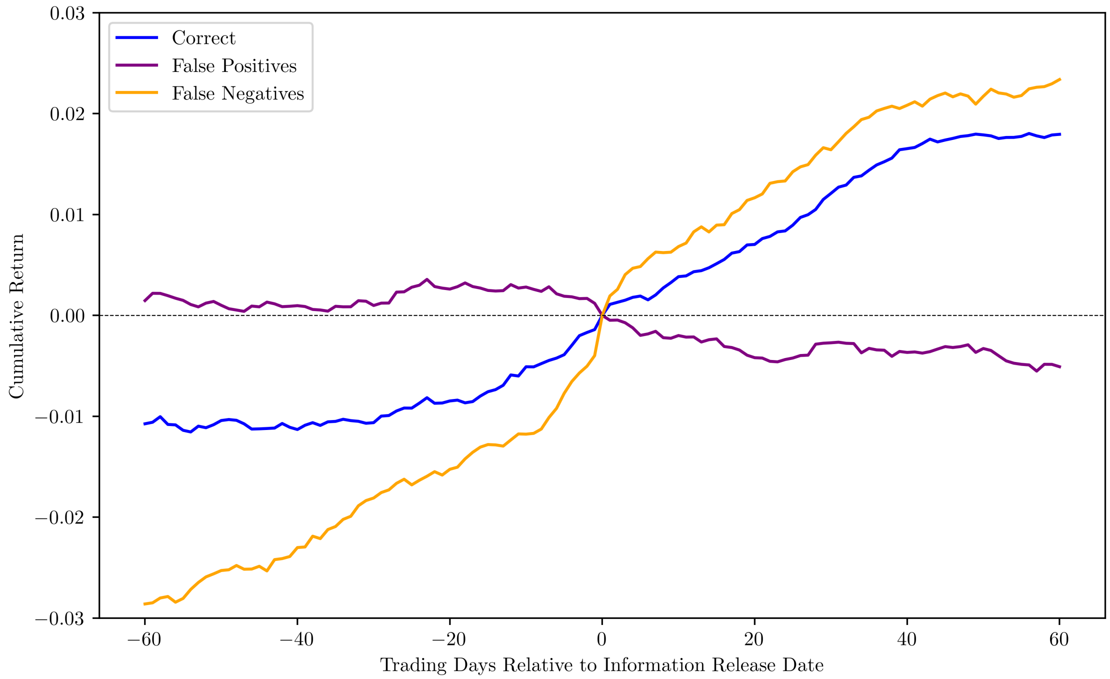


Figure A2. Anomaly Returns with Prediction Models

This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after annual information release dates. The blue line shows the return for the Perfect Foresight model. The green line shows the return for the Martingale model. The purple line shows the return for the Machine Learning model. The returns have been scaled to be zero on the information release date.



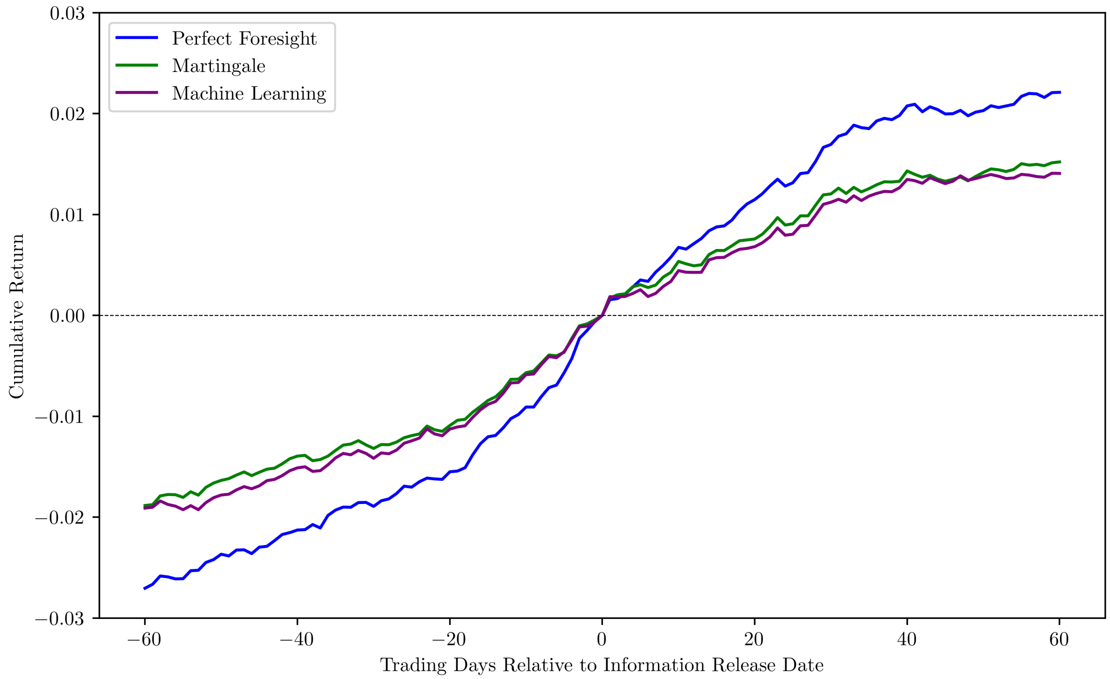
(a) Martingale Model



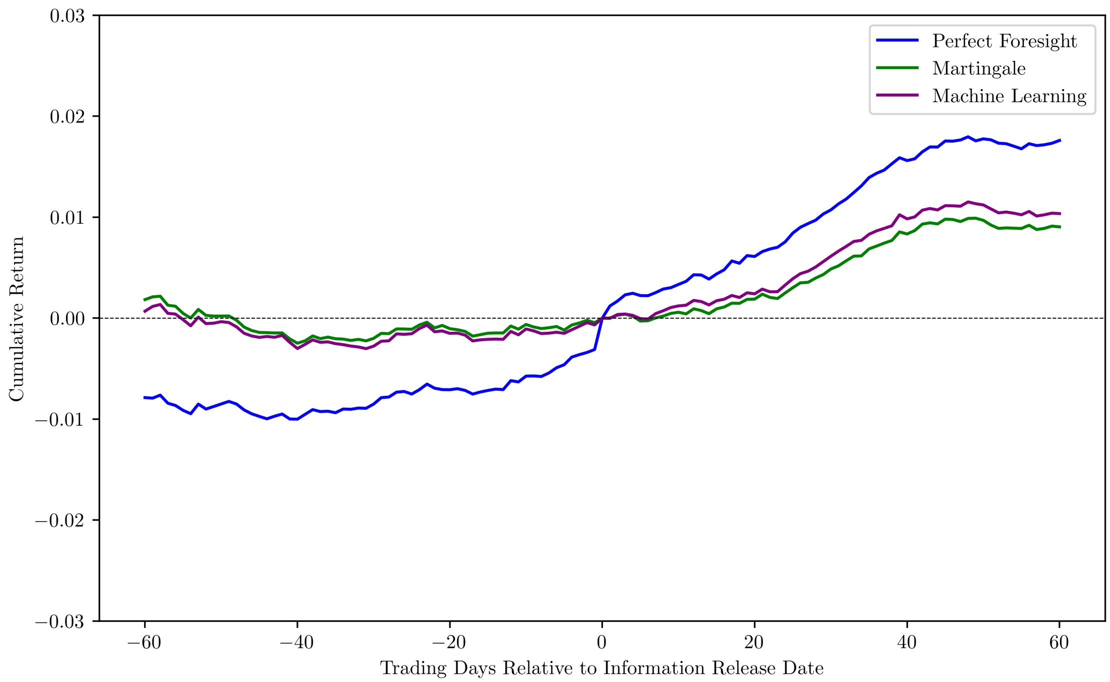
(b) Machine Learning Model

Figure A3. Anomaly Returns for Prediction Outcomes

This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after the information release dates and according to the prediction quality of the model. The blue line shows the return for the correct predictions. The purple line shows the return for false positive predictions. The yellow line shows the return for the false negative predictions. The top panel shows the various returns for the Martingale model while the bottom panel shows returns for the Machine Learning model. The returns have been scaled to be zero on the information release date.



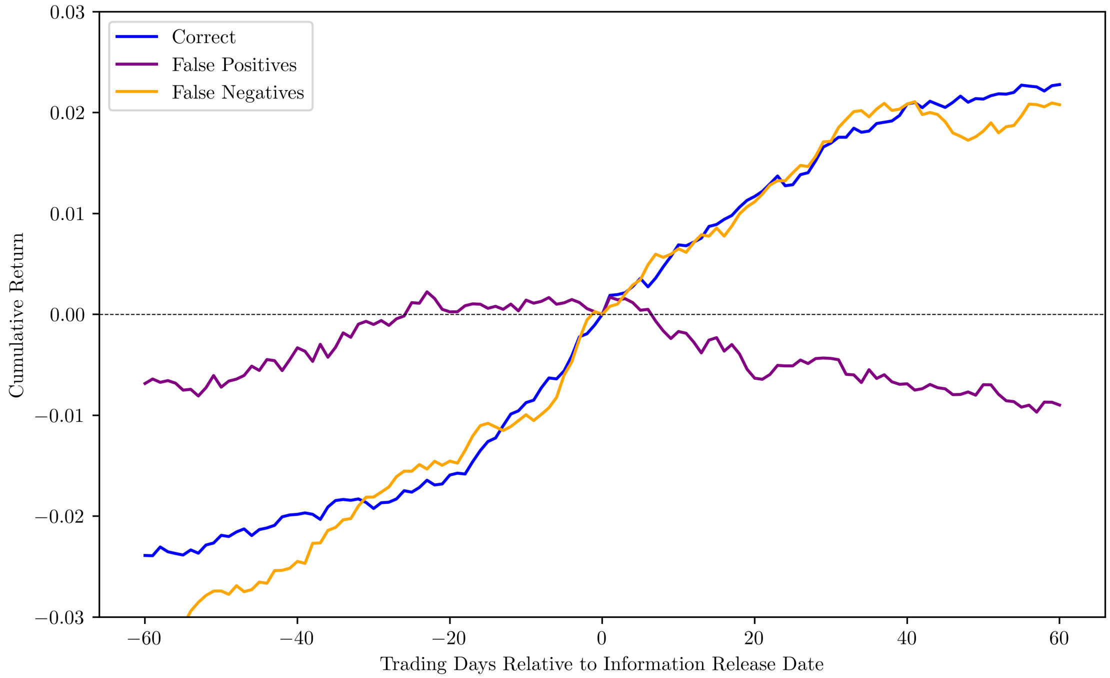
(a) Early Sample Period (1990-2006)



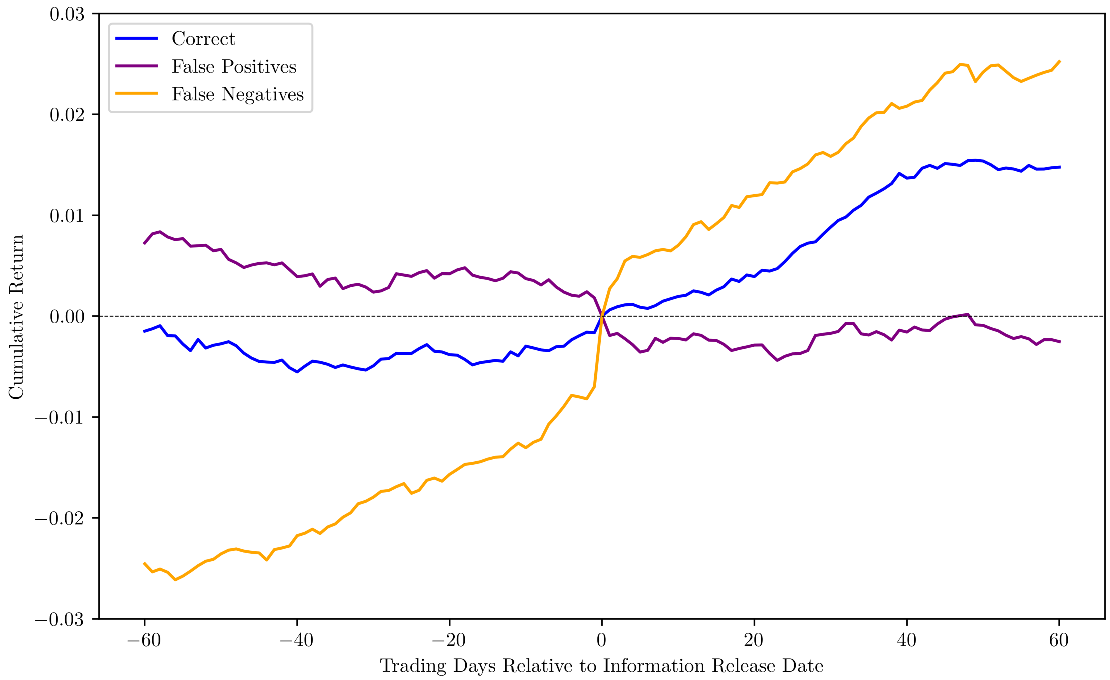
(b) Recent Sample Period (2007-2023)

Figure A4. Anomaly Returns with Prediction Models - Time Trends

This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after annual information release dates and according to the time period. The top panel shows returns over the early part of the sample period (1990-2006) while the bottom panel shows returns over the recent part of our sample (2007-2023). The blue line shows the return for the Perfect Foresight model. The green line shows the return for the Martingale model. The purple line shows the return for the Machine Learning model. The returns have been scaled to be zero on the information release date.



(a) Early Sample Period (1990-2006)



(b) Recent Sample Period (2007-2023)

Figure A5. Anomaly Returns for Machine Learning Prediction Outcomes - Time Trends
This figure shows the compound anomaly returns to the Average anomaly in the 60 trading days (three months) before and after annua information release dates and according to the prediction outcomes from the Machine Learning model and according to the time period. The top panel shows returns over the early part of the sample period (1990-2006) while the bottom panel shows returns over the recent part of our sample (2007-2023). The blue line shows the return for the correct predictions. The purple line shows the return for false positive predictions. The yellow line shows the return for the false negative predictions. The returns have been scaled to be zero on the information release date.

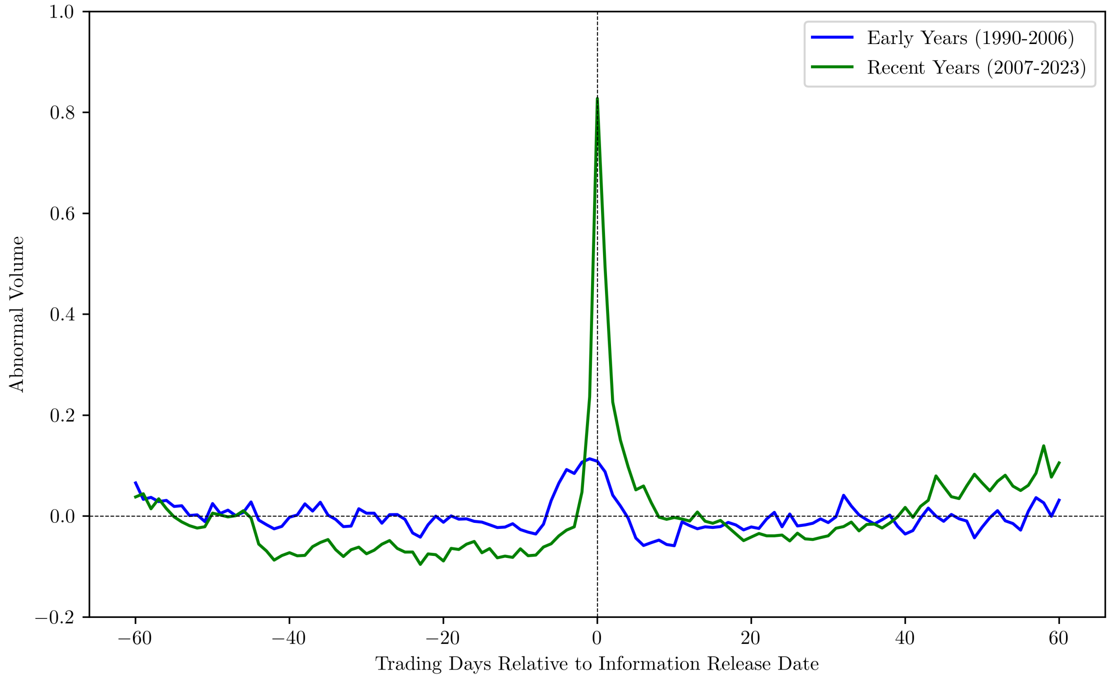


Figure A6. Abnormal Trading Volume - Time Trends

This figure shows the abnormal trading volume for the Average anomaly in the 60 trading days (three months) before and after annual information release dates and according to the time period. The figure shows abnormal volume for the perfect foresight model over the early part of the sample period (1990-2006) and the recent part of our sample (2007-2023).

Table AI. Event Time Returns and Prediction Models

The table shows the event time anomaly returns to the Average anomaly over various time horizons relative to annual information release dates and using various prediction models: the Perfect Foresight Model, the Martingale Model, and a Machine Learning Model. The rows show the additional return from trading before the information release date. The returns are presented as compound returns in basis points and basis points per day. This table is analogous to Table VII.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Perfect Foresight		Martingale		Machine Learning	
Additional return for trading ***before*** the info release date:	Compound Return (bps)	Basis Points per day	Compound Return (bps)	Basis Points per day	Compound Return (bps)	Basis Points per day
1 trading day before	39	19.6	11	5.5	13	6.7
3 trading days before	53	13.2	19	4.9	23	5.7
1 week before	69	11.5	27	4.5	31	5.2
2 weeks before	89	8.1	38	3.4	42	3.8
1 month before	120	5.7	57	2.7	61	2.9
2 months before	161	3.9	77	1.9	84	2.0
3 months before	171	2.8	70	1.2	79	1.3

Table AII. Event Time Returns and Prediction Outcomes

The table shows the event time anomaly returns to the Average anomaly over various time horizons relative to annual information release dates and relative to the outcomes from various prediction models: the Perfect Foresight Model, the Martingale Model, and a Machine Learning Model. The prediction outcomes are Correct, False Positives, and False Negatives. The column Correct records the return to stocks that were correctly predicted to be in the anomaly portfolio at the annual information release date. The False Positives column records the return to anomaly that were predicted to be in the annual anomaly portfolio, but were not (Type 1 errors). The False Negatives column records the return to stocks that were not predicted to be in the annual portfolio but were (Type 2 errors). The rows show the additional return from trading before the information release date. The returns are presented as compound returns in basis points. This table is analogous to Table VIII.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Compound Return (bps)						
	Perfect Foresight	Martingale			Machine Learning		
Additional return for trading ***before*** the info release date:	Correct	Correct	False Positives	False Negatives	Correct	False Positives	False Negatives
1 trading day before	39	29	-25	69	28	-22	68
3 trading days before	53	42	-30	82	40	-23	83
1 week before	69	55	-33	108	53	-26	109
2 weeks before	89	73	-40	134	71	-32	135
1 month before	120	103	-46	167	98	-32	175
2 months before	161	128	-30	256	122	-14	257
3 months before	171	127	-60	297	116	-23	306
Return 3 months ***after***	178	171	-43	198	167	-46	208
N	147,943	108,726	42,601	39,217	105,249	35,338	42,695

Table AIII. Event Time Returns and Prediction Models - Time Trends

The table shows the event time anomaly returns to the Average anomaly over various time horizons relative to annual information release dates and relative to the outcomes from various prediction models: the Perfect Foresight Model (PF), the Martingale Model (Q3), and a Machine Learning Model (ML). The sample is also divided into an early period (1990-2006) and a recent period (2007-2023). The prediction outcomes are Correct, False Positives, and False Negatives. The column Correct records the return to stocks that were correctly predicted to be in the anomaly portfolio at the annual information release date. The False Positives column records the return to anomaly that were predicted to be in the annual anomaly portfolio, but were not (Type 1 errors). The False Negatives column records the return to stocks that were not predicted to be in the annual portfolio but were (Type 2 errors). The rows show the additional return from trading before the info date. The returns are presented as compound returns in basis points. This table is analogous to Table IX with the addition of Panel C.

(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Basis Points Before Info Dates by Prediction Model						
	Early Period (1990-2006)			Recent Period (2007-2023)		
	PF	Q3	ML	PF	Q3	ML
1 trading day before	30	25	29	46	2	4
1 week before	83	56	60	61	8	14
1 month before	176	131	137	83	7	12
3 months before	279	198	201	92	-19	-7
Panel B. Basis Points Before Info Dates by Prediction Outcomes (Martingale)						
	Early Period (1990-2006)			Recent Period (2007-2023)		
	Correct	False Positives	False Negatives	Correct	False Positives	False Negatives
1 trading day before	35	5	14	25	-46	105
1 week before	83	1	82	38	-56	124
1 month before	191	-3	135	46	-74	187
3 months before	260	58	330	30	-138	268
Panel C. Basis Points Before Info Dates by Prediction Outcomes (Machine Learning)						
	Early Period (1990-2006)			Recent Period (2007-2023)		
	Correct	False Positives	False Negatives	Correct	False Positives	False Negatives
1 trading day before	37	11	13	22	-44	107
1 week before	81	7	88	37	-48	124
1 month before	186	12	155	42	-62	189
3 months before	248	80	344	22	-95	276