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INVEST IN PTOs OR DIE TRYING

Achieving Abnormal Returns by Trading Takeover Likeliness

Master's Thesis

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In this Master's Thesis, we examine the potential to achieve abnormal returns by predicting takeover targets within the US market. This study extends on previous literature by aiming to address known issues that dilute the returns of takeover prediction strategies, such as prediction errors, timing issues, and the misclassification of distressed firms as potential targets. By utilizing advanced machine learning techniques, including random forest and gradient boosting, along with a monthly forecasting framework and new variables, we are able to notably enhance predictive accuracy as well as generate abnormal returns.

Our approach introduces a framework to differentiate between various levels of firm risk, using measures such as Distance to default and Safety, which improves the model's performance and provides deeper insights into the characteristics of potential takeover targets. Additionally, we apply subcomponents of the Quality factor developed by Asness et al. (2018) to enhance our model's predictive power. Doing so we improve model accuracy but also find that firms with higher risk profiles, albeit not in distress, are more likely to be takeover targets.

Our best models beat random selection by a magnitude of nearly three times – a clear improvement to previous literature. Correspondingly, we find that all our models overperform the market and generate significant abnormal returns. We also introduce a long-short strategy to isolate pure PTO-driven returns. Our long-short strategies yield significant abnormal returns and achieve near factor-neutrality in the Fama-French three and momentum framework.

In conclusion, while predicting takeovers remains challenging, our research demonstrates that it is possible to achieve abnormal returns with takeover prediction models. This study not only timely revisits the topic of takeover prediction but also offers practical applications for investment strategies based on takeover prediction, as well as new insights on the characteristics of PTO targets.

Keywords takeover prediction, investment strategy, abnormal returns, machine learning, firm risk, market sentiment, Quality factor, Distance to default, hedged strategies

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Tämä tutkielma keskittyy selvittämään, mikäli sijoitusstrategia, joka perustuu pörssilistattujen yritysten ostotarjousten ennustamiseen Yhdysvaltain markkinoilla, voi tuottaa ylisuuria tuottoja. Tutkimus pyrkii käsittelemään tunnettuja ongelmia, jotka heikentävät yritysostoennustestrategioiden tuottoja kuten ennustusvirheitä, ajoitusongelmia ja maksukyvyttömien yritysten virheellistä luokittelua potentiaalisiksi kohteiksi. Hyödyntämällä edistyneitä koneoppimistekniikoita yhdessä kuukausittaisen ennustekehyksen ja uusien muuttujien kanssa kykenemme selkeästi parantamaan ennustetarkkuutta sekä tuottamaan ylisuuria tuottoja.

Lähestymistapamme esittelee ostokohteiden riskitasoja erottelevan kehyksen, joka parantaa mallin suorituskykyä ja tarjoaa syvempää ymmärrystä potentiaalisten yritysostokohteiden piirteistä. Lisäksi sovellamme Asness et al. (2018) kehittämiä Quality-tekijän osakomponentteja parantaaksemme malliemme ennustusvoimaa. Parannuksemme lisäävät mallien tarkkuutta ja samalla havaitsemme, että yritykset, joilla on korkeampi riskiprofiili mutta jotka eivät kuitenkaan ole välittömän konkurssiuhan alla, ovat todennäköisempiä yritysostokohteita.

Parhaat mallimme ylittävät satunnaisvalinnan lähes kolminkertaisella marginaalilla, mikä on selvä parannus aiempaan kirjallisuuteen verrattuna. Vastaavasti havaitsemme, että kaikki mallimme ylittävät markkinatuotot ja tuottavat merkittäviä ylisuuria tuottoja. Esittelemme myös lyhyeksi myyntiä hyödyntävän strategian, jonka avulla pyrimme eristämään puhtaista yritysostotarjouksista juontuvia tuottoja muista riskialtistumisista. Lyhyeksi myyntiin pohjautuvat strategiamme tuottavat tilastollisesti merkitseviä ylisuuria tuottoja ja saavuttavat lähes neutraalin riskisuhteen Fama-French kolmifaktorimallin ja momentum-kehyksen puitteissa.

Vaikka yritysostojen ennustaminen on haastavaa, tutkielmamme osoittaa, että yritysostoennustemallien avulla on mahdollista saavuttaa ylisuuria tuottoja. Tämä tutkimus ei ainoastaan täytä ajallista aukkoa kyseissä tutkimushaarassa vaan tarjoaa myös uusia käytännön sovelluksia yritysostoennustamiseen perustuville sijoitusstrategioille sekä uusia näkemyksiä yritysostokohteiden ominaisuuksista.

Avainsanat ostotarjous, ylisuuret tuotot, koneoppiminen, Quality, Distance to Default, lyhyeksi myynti

Contents

1. Introduction

1.1 Motivation and research question

On January 17th 2024, Efecte, a Finnish cloud-based service management software solution provider, received a friendly cash offer for all of its outstanding shares and options. The offer price was set at EUR 15, representing a 91% increase over the last quoted price prior to the announcement. Consequently, upon the announcement, Efecte's share price surged from EUR 7.86 to EUR 14.75, reflecting an approximate 88% rise within seconds. Such high and fast returns are always a delightful sight for an investor's eye, however, more often than not, only available when a public takeover (PTO) bid is published, and one is lucky enough to be an owner of the stock.

Thus, the question arises – could one try to predict such lucrative announcements, and if so, could one build a successful investment strategy around such predictions? In other words, invest in firms with modelled high probabilities of takeover in hopes of being right sufficiently often.

Academic research has been contemplating this question since at least the 1960s with varying results to date. The consensus leans towards the inability to do so, though the question remains open for further exploration. Earlier papers have failed to build meaningful investment strategies, however, in the past 10 years, research has found at least some evidence that takeover prediction can be used to gain abnormal returns.[1]

This paper studies takeover prediction-based investment strategies motivated by the absence of recent academic work focusing on takeover predictions and the related investment strategies in the US market. Further, despite no conclusive answers being established in past studies, the persistently high levels of merger and acquisition (M&A) and takeover activities[2] over the last decade further underscore the relevance and timeliness of revisiting this topic. Furthermore, several areas for improvement exist in the field as explained below. Hence, the aim of this study is to investigate, whether it is possible to generate abnormal returns, by avoiding the issues known to have diluting impact on returns of takeover prediction strategies.

[1] For instance, Danbolt et al. (2016)

[2] Peak for M&A activity was reached in 2021 (1985 – 2023) (IMAA, 2024). See Section 4.2 some 50 to 150 takeovers were performed yearly between 2010 and 2023

One of the most recent studies on the subject, by Danbolt et al. (2016), re-examines whether portfolios of predicted takeover targets can be utilised to build a viable investment strategy with UK data. The study argues that prediction errors, poor timing, and the misclassification of bankrupt firms as potential targets have principal effect in diluting returns.

Building upon Danbolt's findings, we conduct a thorough examination of previous research to identify key areas of improvement. Consequently, we propose corresponding methods to address these key issues, and test their performance as outlined below.

First, most previous literature employs bi-yearly or yearly observations which renders prediction periods much longer than necessitated by today's computing power and data availability. Thus, altering models to monthly specification could yield new, different results.

Second, only a few new explanatory variables used for forecasting have been introduced in a takeover prediction setting in the past two decades or so. Moreover, these variables are often simple in comparison to other fields of financial prediction literature. Thus, we test whether sub-components of the so-called Quality factor (Asness et al., 2018) would function better in takeover prediction than less developed variables used before. Furthermore, to decrease timing-related issues we include variables for market sentiment as well as technical metrics based on share price momentum and trading volume.

Third, only simple screens have been used to minimize issues related to distressed companies being misclassified as targets. A large body of literature exists in the field of bankruptcy prediction which can be well utilized in this context as well. Consequently, we build a new variable, called firm risk to proxy differences in the riskiness of potential takeover targets.

Fourth, logistic regression has traditionally been the predominant methodology for modelling takeover likelihood. In recent years, the availability of advanced machine learning models has increased, making these sophisticated methods more accessible. Consequently, we experiment with these advanced modelling techniques.

1.2 Main results on predictive capability

In terms of predictive accuracy, we find that utilizing more advanced modelling techniques, such as gradient boosting and random forest, or forecast combination, notably increases predictive performance. By forecast combination, we refer to a technique in which the outputs of multiple models are used to form a final prediction. We, however, find that merely increasing the number of predictive variables does not notably improve the performance of the prediction model, and that enhancing the predictive power of explanatory variables is challenging.

Nonetheless, we find that the inclusion of our additional hypothesis, *firm risk*, enhances the model's ability to distinguish between actual targets and distressed entities - a significant challenge in earlier studies. Moreover, by adopting a monthly framework and incorporating technical variables such as price momentum we are able to enhance the model's timing capabilities.

Promisingly, all models beat random selection to a magnitude nearly double, with the best model being more than 3.3 times better than random selection. All in all, our models demonstrate a clear improvement over the results documented in prior studies.[1]

1.3 Main results on portfolio performance

Based on predictions from our takeover models, each month we form portfolios that invest in 25-100 firms with the highest estimated probabilities of receiving a PTO bid during the next month. Our strategy spans from 2004 to 2023.

In terms of portfolio performance, we find that all three tested models are able to outperform the market and generate significant abnormal returns in the Fama-French three and momentum framework in a long-only setting (abnormal returns ranging from 0.3% to 1.0% monthly). Furthermore, we find that two of the three models tested also benefit from superior firm selection, thereby enhancing the strategy's returns through non-PTO-related exposures. On the contrary, the average returns from PTO hits are quite consistent across all models.

Consequently, as our research is primarily focused on capturing PTO returns, we attempt to isolate pure PTO-driven returns by building a long-short strategy. Essentially, by going long on few of the most likely PTO targets in one industry and shorting a larger number of similar firms, we aim to capture returns driven solely by PTOs. All three long-short models generate statistically significant abnormal returns (ranging from 0.4% to 0.9% monthly) and achieve near factor-neutrality in the Fama-French three and momentum framework. All in all, our

[1] Compared to Brar et al. (2009), Ouzounis et al. (2009) & Danbolt et al. (2016)

results give strong grounds for the viability of long-short PTO prediction investment strategies.

1.4 Contribution to existing literature

Our research contributes to existing literature in multiple ways. Firstly, our additional hypotheses not only improve model performance but also provide deeper insights into the characteristics of potential takeover targets. To our knowledge, our approach is the first of its kind, using two risk measures (Distance to default and Safety) to differentiate between various levels of firm risk. Previous literature suggests that PTO targets are companies with high leverage and low liquidity. Our framework reveals that PTO targets are, on average, firms with higher risk profiles, provided they are not currently experiencing immediate distress.

In addition, our paper is to our knowledge the first to incorporate the Quality measure by Asness et al. (2018) into takeover prediction. More specifically, we test whether using sub-components of the so-called Quality characteristic (Asness et al., 2018) would function better in takeover prediction than less developed variables used before. Doing so, we find that although riskier, PTO targets are also found to be of higher overall Quality. These distinctions raise questions on how well not only the drivers behind PTO activity but also the ideal features of PTO targets are understood.

In addition, our paper is among the very first to adopt a monthly forecasting period and the first to utilise the latest machine learning algorithms. We are also the first to form a long-short strategy that seeks to isolate pure PTO-driven returns. Furthermore, our study is one of the firsts that seek to include all available firms into consideration – most studies employ small samples, rendering their results incomparable to possible real-world performance.

Lastly, the study has future implications for takeover prediction. Our findings reveal that the selected model framework has more impact on predictive performance than variable selection, and thus, future studies should focus on the classification problem from a technical point of view. Furthermore, as we show that even with a very basic short leg, other non-PTO exposures can be essentially traded away, further research would also benefit from the development of better short legs.

The rest of this paper is structured as follows. In Section 2 we first discuss previous literature as well as key identified areas of improvement in the field. In Sections 3 and 4 we discuss the data and forecasting strategies used in this study. Consequently, in Section 5 we discuss variables used for forecasting takeover targets. Finally, in Section 6 we evaluate the developed takeover prediction models and formulate investment strategies based on the models. In Section 7 we conclude our paper.

2. Prior literature

As mentioned above, the aim of this study is to investigate whether it is possible to generate abnormal returns with a takeover prediction strategy by avoiding issues known to have a diluting impact on the returns. Thus, in this literature review, we seek to identify areas for improvement for such key issues (prediction errors, timing, distressed assets). To do so we first discuss previous literature in Section 2.1, and consequently, discuss identified areas of improvement in Section 2.2.

Please note that this field of literature uses the word "hypothesis" to describe a characteristic believed to impact takeover likeliness. The word "variable" is used to describe a measurable feature that is used to quantify the impact of a hypothesis.

2.1 Literature on takeover target prediction

Literature on takeover prediction can be categorized into four unique periods based on significant similarities in focus and conclusions as put by Tunyi (2021). The first era (1968-1985) focuses primarily on identifying common traits among takeover targets, often utilizing financial ratios for this purpose. The second era (1986-2002) focuses on developing predictive models and introducing formal target prediction hypotheses. The consensus from this period was, however, that creating a profitable investment strategy based on the prediction of takeover targets is unfeasible.

The third era (2003-2009) revisited similar research questions through the application of new modelling techniques, ultimately corroborating previous findings that the prediction accuracy for identifying takeover targets was constrained. Nonetheless, this period provides some indications of potential abnormal returns.

In the fourth era (2010-present) a portion of studies focus on improving prediction performance. Others study why recent IPO firms become quickly PTO targets, while some focus on understanding the effects of M&A predictability on various financial aspects, such as share valuation, and PTO market anticipation. Such papers are largely out of the scope of our paper. Importantly, this era provides further evidence suggesting that takeover prediction, when paired with suitable models and screens, could indeed generate abnormal returns.

2.1.1 First era of takeover prediction: 1968-1985

Research into takeover prediction is initiated by Taussig and Hayes (1968). By conducting a univariate analysis on a set of accounting variables they find that poor operating performance, characterised by excessive liquidity, poor earnings, and an erratic dividend policy are more likely proxies for takeover likeliness.

The pioneering study by Wansley, Roenfeldt and Cooley (1983) appears to be the first to develop an investment strategy centred around predicting takeover targets. Employing a discriminant analysis framework and a set of financial variables (e.g., firm size, leverage, P/E) they develop a financial profile for acquired firms. A portfolio of companies that fit well in this profile (likeliness of acquisition) is then selected for purchase. Interestingly they find that such portfolios produce risk-adjusted annual returns ranging from 5 to 28 percent for different holding periods between March 1977 and December 1978.

Dietrich and Sorensen (1984) are the first to apply a logit framework rather than an MDA approach. They find that the management's ability to create sales per unit of asset is the most influential factor affecting merger likelihood. The low asset turnover must, however, be accompanied by any or a combination of low equity pay-out, low leverage, high trading volume, or small size to produce a high probability of merger. Moreover, they find that the P/E ratio does not have a significant effect on merger likelihood.

Moreover, Hasbrouck (1984) also finds evidence supporting the notion that management's competence has an impact on takeover likeliness. The study introduces *q* (market value / replacement value) as a new explanatory variable and finds that a low *q* is associated with a higher likelihood of takeover. A low *q* could indicate poor managerial performance or misvaluation.

2.1.2 Second era of takeover prediction: 1986-2002

The second era (1986-2002) focuses on developing predictive models and introducing formal target prediction hypotheses. The era begins with Palepu (1986), a pioneering study that to date remains at the core of takeover prediction research. The paper tries to correct various methodological flaws which are argued to cause bias in the results of the first era's research.

More specifically, Palepu (1986) argues that there are three key issues in preceding literature that render their prediction accuracy erroneously too high: 1) the utilisation of non-random equal weight samples without proper adjustment of explanatory variables, 2) the use of arbitrary, context independent, probability cut-off points in target prediction, and 3) the employment of equal weight samples in prediction tests. For instance, Monroe and Simkowitz (1971) report that their model correctly predicts 83% of targets and 72% of non-targets in the estimation data and 64% / 61% in the test sample. To correct for the abovementioned issues, Palepu (1986) employs a logit model together with a maximum likelihood estimation approach. Further, the paper uses a larger group of firms that better resembles the whole population of firms. Furthermore, Palepu uses cutoff probabilities (used for investment decisions), which are derived from the model's estimated probability distributions for the two groups (target and non-target firms), which in turn means that a minimization-of-errors criterion is utilized giving each error type's similar cost (misclassification of non-targets as targets and incorrect prediction of a target as a non-target).

Furthermore, Palepu (1986) is the first to introduce prediction hypotheses that are grounded on economic theory: inefficient management, industry disturbance, size, market-to-book, and price-to-earnings. Using U.S. data from 1971 to 1979, Palepu (1986) finds that the hypotheses, though found statistically significant, lead to a model with limited explanatory power combined with generally small estimates of acquisition probability. The model is tested on a group of 1117 U.S. firms in 1980. The model correctly classifies 24 of the 30 (80%) actual targets and 486 of the 1087 (45%) actual non-targets. Thus, despite accurately identifying a high proportion of actual targets, the model mistakenly classifies many non-targets as targets. Consequently, investing in companies identified by the model as potential acquisition targets does not yield significant abnormal returns. Later studies (e.g., Powell, 2001) go on to agree with Palepu's methodological points, however, also challenge Palepu's use of the minimization-of-errors criterion used for investment decisions, and the assumption that both misclassification of non-targets as targets and incorrect prediction of a target as a non-target would be equally costly in the context of takeover prediction.

Ambrose and Megginson (1992) extend on Palepu (1986) by including measures of insider and institutional shareholdings, takeover defences, and tangible assets. Utilizing a sample of 169 U.S. targets and 267 non-targets between 1981 and 1986, the study finds that takeover likelihood is positively related to the amount of tangible assets, and negatively related to firm size and to the net change in institutional holdings. They find some evidence that the presence of a voting rights defence is positively related to takeover likelihood and that the presence of blank-check stock authorizations is negatively related to takeover likelihood. Lastly, they find that the model used by Palepu (1986) loses some explanatory power in their time period.

Barnes (1990) and Barnes (1998) extend on Palepu (1986) by attempting to further highlight other methodological weaknesses present in takeover prediction, especially concerning the use of multivariate predictive models. Barnes argues that financial ratios can fluctuate due to changes in price levels, accounting practices, and economic cycles, as well as differ across industries, causing issues in data stability and thus in modelling: an effective predictive model maintains consistency over time and across various sectors. To address the issue Barnes suggests employing industry-relative predictive analyses. Even though industry-relative models are found to perform better, Barnes fails to powerfully identify takeover targets. The question of industry-relative variables goes on in further research being eventually left open as performance varies per sample and study.

Moreover, Barnes (1998) argues that a predictive model that integrates changes in share prices with accounting figures, serving as indicators of economic factors influencing merger bid likelihood, is expected to outperform a model relying solely on one of these elements. This is based on the notion that price changes could possibly occur due to early purchases by insiders anticipating a future merger bid. This activity could occur simultaneously with the bidder's initial consideration or during early discussions between the two firms. As the price adjustment likely occurs over a relatively long period, it would not be incompatible with the efficient capital market hypothesis. Nonetheless, predictive accuracy did not enhance with the inclusion of share price changes. A probable reason is that the majority of the total share price movement due to a merger bid occurs just before the announcement, typically in the month leading up to it (Barnes, 1998).

Finally, Barnes (2000) builds on Barnes (1990) and Barnes (1998) by employing an UK sample to test how different models compare to the enhanced models described above. After testing various modelling techniques (logit and IDA) and model specifications Barnes concludes that abnormal returns are likely impossible to be achieved in the UK (1991-1994) with historical cost accounting data.

Walter (1994) builds on Wansley, Lane and Yang (1983) and Palepu (1986) by studying differences between logit models ran on current cost data in comparison with historical cost data between 1981 and 1985. Walter (1994) demonstrates that using current cost accounting data in the U.S. yields relatively high predictive accuracy, better than historical cost data.

However, due to the financial losses incurred from several inaccurate predictions, the model achieved only modest overall excess returns on a portfolio level.

Powell (1997) extends on Palepu (1986) by employing similar hypotheses, however, along with a multinominal framework and a sample of 411 targets and 532 non-targets between 1983 and 1991. Powell (1997) suggests that hostile and friendly targets have different characteristics, and thus, using a binominal framework could lead to misleading conclusions on the impact of underlying factors driving takeovers. Furthermore, Powell (1997) finds evidence that in addition to firm-specific factors, also industry-specific factors impact takeover likeliness and that characteristics affecting takeover likeliness change over time. Furthermore, Powell (1997) contends that the hypotheses of Palepu (1986) which are frequently used in predictive modelling across numerous studies, are either not valid or are poorly represented by employed variables, as such models lack explanatory power in their sample. This notion is further supported by Barnes (1998) who also suggests that models built on Palepu (1986) are ineffective in predicting targets, and thus not able to create abnormal returns.

Powell (2001) continues by also testing whether a takeover prediction model based on Powell (1997) can be used to generate abnormal returns. The main difference to Palepu (1986) methodology is that rather than using cut-off probabilities that are derived from the model's estimated probability distributions for the two groups (target and non-target firms), one should attempt to build a strategy for determining optimal out-of-sample cut-off probabilities, which takes into account the investment objective of prediction modelling (different cost of type I and type II errors). In other words, the loss for the misclassification of a non-target firm is smaller than the pay-off from the correct classification of a target.

To apply this logic Powell (2001) introduces a portfolio selection scheme in which the proportion of target firms is maximized. More specifically, ten portfolios are constructed by sorting each firm in the estimation sample in descending order by its probability of takeover. Consequently, the classification rule for the prediction sample is derived from the portfolio that has the highest concentration of target firms in the estimation sample. To test whether the suggested improvements increase the strategy's profitability, Powell (2001) estimates model parameters using an equal-share UK-based sample with both 471 targets and non-targets. Consequently, Powell tests the constructed model out-of-sample using data for 1000 companies in 1996. The best model ends up predicting only 3.24% targets into the final portfolio, which in the sample translates to significant losses.

2.1.3 Third era of takeover prediction: 2003-2009

The third era (2003-2009) revisited similar research questions through the application of new modelling techniques, ultimately corroborating previous findings that the prediction accuracy for identifying takeover targets was constrained. Nonetheless, this period provides some indications of potential abnormal returns. Alternative, perhaps more advanced, modelling approaches are seen essential in addressing the significant prediction inaccuracies documented in prior studies, which explains the rise in new modelling techniques in the third era.

The era is started by Espahbodi and Espahbodi (2003) who test logit, probit, discriminant, and recursive partitioning models to predict takeovers with a sample of 133 US PTOs in the last six months of 1997. The takeovers are paired with up to three non-target control firms at random from all firms listed in the Disclosure database with the same fiscal year and similar SIC code. In addition to using financial variables similar to those initially proposed by Palepu (1986), Espahbodi and Espahbodi (2003) include several non-financial variables such as anti-takeover regulation, the presence of poison pills and golden parachutes, and insider ownership. Of the variables, free cash flow to total assets, golden parachute dummy, takeover regulation dummy, and equity market value to total firm value are found most significant in a stepwise elimination procedure. Discriminant, logit, and probit models accurately identified approximately 62% of target firms and 61% of non-target firms. In contrast, the recursive partitioning model demonstrated higher accuracy, correctly classifying 89% of target firms and 88% of non-target firms (accuracy, however, decreases significantly in validation tests). All in all, the results indicate that even after model enhancements it is difficult to predict corporate takeovers, however, they do not derive investment returns for their predictions.

Powell (2004) builds on Powell (1997) and Powell (2001) by utilizing a multinominal framework for differentiating between hostile and friendly targets. A portfolio selection scheme that maximizes the proportion of target firms is utilized as introduced by Powell (2001). A dataset of 9,891 UK firms between 1986 and 1995 is employed for the estimation period and 1,000 firms in 1996 for testing. Powell (2004) contends that multinominal models significantly outperform binominal models in terms of the percentage of targets correctly predicted, however, even after improvements the models continue to misclassify a high proportion of non-target firms as targets with even the best model performing only marginally better than random selection.

All in all, Powell (2004) fails to generate abnormal returns with all strategies but one that focuses solely on investing in hostile targets. Upon further investigation, they find that correctly predicted hostile firms, together with misclassified hostile targets, generate significant positive abnormal returns. For contrast, in a binominal and friendly-only portfolio a large share of portfolio returns is wiped out by investing in non-targets classified as targets. This phenomenon can potentially be explained by the characteristics of general takeover targets, as especially those involved in friendly takeovers resemble those of firms facing financial difficulties - characterized by smaller size, reduced liquidity, and increased leverage. Conversely, targets of hostile takeovers tend to be larger, which means the multinominal model inherently 'screens out' firms more prone to financial distress, resulting in a portfolio that yields positive abnormal returns. (Powell, 2004) It must, however, be noted that the study uses a very small sample of hostile targets, which might affect the results.

Powell and Yawson (2007) study whether corporate restructuring is generally driven by common factors. As common factors, they employ the variables often used in takeover prediction (Ambrose & Megginson, 1992; Palepu, 1986; Powell, 2004) to test whether they also explain other restructuring events, including divestitures, bankruptcies, and significant employee layoffs. This is done to test whether the large share of errors often prevalent in takeover prediction is due to modelling takeovers in isolation from other events. Using a multinominal framework and a sample of 9,573 UK firms between 1992 and 2002, Powell and Yawson (2007) find evidence that factors often used in takeover prediction also explain other restructuring events. In particular, previous stock market performance, growth, and leverage seem to act as common underlying factors, which implies that factors often used in takeover prediction might not capture the unique features of takeovers. All in all, the addition of other restructuring events into the multinominal framework is found to decrease misclassification, although not entirely. Furthermore, their results suggest that target and distressed (or bankrupt) firms share common firm characteristics. No investment returns are calculated based on their model.

Ouzounis et al. (2009) explore the use of four non-parametric methods (UTADIS, support vector machines, discriminant analysis, artificial neural network) as well as their combination in takeover prediction investment strategies. Their models utilize seven variables commonly employed in takeover prediction. Using a sample of entities listed on the LSE between 2001 and 2005, they suggest that non-parametric techniques might be superior in comparison to other methodologies tested in the paper. Best results are achieved with a portfolio constructed based on an absolute voting (AV), rule in which an investment decision is only taken if all individual models classify a firm as a target, as well as a simple model based on

UTADIS. Interestingly, returns between portfolios based on UTADIS and AV are found highly similar even though the portion of target companies formed with the strategies differ: both are able to generate abnormal returns in most holding periods. All in all, the paper finds evidence that the concentration of correctly forecasted bid targets in each portfolio does not necessarily imply better performance, as expected by most papers regarding the topic. This lends evidence to the notion that prediction models might be able to capture firms that bear great resemblance with actual acquired companies, which in turn allows the incorrectly predicted targets to contribute positively or at least neutrally to the portfolios' performance.

UK studies Pasiouras and Tanna (2010) and Pasiouras et al. (2007) focus on the identification of targets in the EU banking industry. Pasiouras et al. (2007) focus on comparing the relative efficiency of multi-criterion approaches (MHDIS, PAIRCLAS, UTADIS) with all models developed and tested using 10-fold cross-validation. Pasiouras et al. (2007) conclude that a fair amount of misclassification still occurs, but that such advanced models can, in fact, perform better.

Brar et al. (2009) extend on Palepu (1986) and Barnes (1998) by including technical measures such as price momentum, and trading volume as well as market sentiment into a logit framework with a sample of some 900 European cross-border targets. As expected by previous findings the targets are smaller in size, undervalued, less liquid, and experience lower growth, but also exhibit strong short-term price momentum and active trading prior to bid announcement. Investing in the top 10% of companies with the highest likelihood of being taken over yields a total return of 17.4%, based on a 1-month holding period. The model can correctly predict 107 out of 540 takeover candidates, however, the model successfully picks a higher number of targets which are taken over later on. Thus, the strategy benefits from significant pre-announcement outperformance, even if it predicts a target too early.

2.1.4 Fourth era of takeover prediction: 2010-present

A portion of papers in this era focus on improving prediction performance. Others study why recent IPO firms become quickly PTO targets, while others focus on understanding the effects of M&A predictability on various financial aspects, such as share valuation, and PTO market anticipation. Such papers are, however, out of the scope of this paper. Importantly, this era provides further evidence suggesting that takeover prediction, when paired with suitable models and screens, could indeed generate abnormal returns.

Cremers et al. (2009) study the impact of takeover likelihood on firm valuation. They argue that all things equal, firms exposed to takeovers have different risk profiles than those that are not. This is based on the notion that if firms are more likely to be acquired in times of greater free cash flow or lower required returns, the targets become more vulnerable to fluctuations in cash flows or changes in the risk premium (and thus have more risk). Thus, cash available and the price of risk form two state variables that describe time variation in expected returns, which in turn the takeover factor is a proxy for.

To form a takeover factor, Cremers et al. (2009) employ a logit regression with US-based targets and a number of independent variables commonly used in takeover prediction. Firms are then sorted into quintile and decile portfolios based on their takeover vulnerability. Consequently, Cremers et al. (2009) develop a "takeover factor" by purchasing (or selling) firms with a high (or low) probability of being acquired. They show that the so-called "takeover factor" is able to significantly improve the four-factor model in cross-sectional equity returns, lending evidence to the argument that takeover risk is more an unidentified source of risk rather than mispricing. Further, they verify that their takeover factor is indeed related to takeover vulnerability rather than a more general exposure to business cycles. This is accomplished by examining changes in a firm's takeover beta before and after state anti-takeover legislation is enacted in the state of the firm's incorporation. Consistent with their model, takeover betas decline after such legislation is implemented, indicating that firms undergo an exogenous shock that diminishes their susceptibility to takeovers. All in all, they find that both mean and abnormal returns generally increase with the likelihood of takeovers.

Rodrigues and Stevenson (2013) and Danbolt et al. (2016) both focus on improving takeover prediction modelling, however, taking highly different approaches. Rodrigues and Stevenson (2013) use combinations of forecasting models (logistic, neural networks) to determine a methodology that would reduce takeover classification errors. The use of such "forecast combination" methodologies is seen as an effective way of increasing forecasting performance offered by single models. A combined forecast is produced by a function that compiles outcomes from various takeover prediction models, utilizing inputs from both neural network and logistic modelling techniques. Rodrigues and Stevenson (2013) find that a combined approach outperforms any single model in their study and generates abnormal returns of high magnitude. Moreover, the results of the combined model remain stable over time, demonstrating the reliability of this methodology in achieving a lower misclassification error.

Danbolt et al. (2016) re-examine whether portfolios of predicted targets can be utilized to build a profitable investment strategy with 2,799 UK targets between 1988 and 2011 and a logit framework. The study argues that the following three issues have principal effects in diluting returns of such strategies: prediction errors, poor timing, and the misclassification of bankrupt or soon-to-be firms as potential targets. The study is able to find evidence for all three arguments but only able to find viable solutions for the misclassification problem.

Danbolt et al. (2016) adopt various screenings to avoid investing in distressed companies, namely screening based on the Taffler Z-score, size, leverage, and liquidity. Further, merger rumours are included to assist with timing, and additional variables (industry concentration, blockholders, price/trading momentum, market sentiment) to assist with prediction.

All in all, Danbolt et al. (2016) find that the enhanced model with additional variables does not perform better than the conventional model. Merger rumours are also found inefficient in improving timing-related issues. Lastly, Danbolt et al. (2016) suggest that a straightforward screening strategy based on size, leverage, and liquidity can substantially reduce the adverse impacts of bankrupt and distressed firms in target portfolios. Such portfolios are found to generate significant abnormal returns of up to 0.9% per month.

De Jong and Fliers (2020) and Meghouar and Ibrahimi (2020) both focus on predicting takeover targets in smaller economies, namely France and the Netherlands. However, neither of the papers calculate investment returns based on their models. Meghouar and Ibrahimi (2020) conduct their analysis on a sample of 128 French listed companies, comprising of 64 targets and 64 non-targets. The study uses Wilcoxon–Mann–Whitney tests and logistic regression to evaluate nine hypotheses. These include seven common financial hypotheses (Palepu, 1986) and two new variables: growth options and shareholder value creation. The findings indicate that companies offering growth opportunities but failing to convert these into investments are prime takeover targets. Additionally, companies exhibiting low value creation or even value destruction, as indicated by Economic Value Added (EVA), are more susceptible to takeovers due to conflicts of interest between managers and shareholders.

Moreover, De Jong and Fliers (2020) apply a logit framework to a sample of 200 Dutch takeovers between 1961 and 2008. Beyond the standard variables frequently employed in takeover prediction, this study also incorporates takeover defences and blockholder presence as explanatory variables. The findings suggest that up until the mid-1980s, target companies typically had low debt levels and high cash reserves. Following this era, smaller and more profitable companies became prime targets for acquisition. In recent times, the adoption of takeover defences have effectively protected firms from being acquired, a trend not observed in the period leading up to the mid-1980s.

Table 1 – Summary of annualized abnormal returns from takeover literature post-2000

This table summarizes the results of previous studies that employ an investment strategy based on takeover prediction. Models used in papers published before 2000 do not generally generate abnormal returns. Irrespective of the reported return period length, all returns are adjusted to an annual format for comparison. Most papers do employ comprehensive asset pricing frameworks, which might impact results.

Study	Annualized abn. ret.	Data	Investment period	Other information
Powell (2001)	-11%***	UK 1986-1995	12 months	Portfolio of 216 predicted targets of which 3.2% were actual targets. Portfolio constructed at the start of 1996.
Powell (2004)	7.0%	UK 1986-1995	12 months	Portfolio of 117 hostile targets of which 7 are actual targets. 110 misclassified targets also generate abnormal returns. No CAR with strategies that include friendly targets. Portfolio constructed at the start of 1996. Return significance not defined.
Brar et al. (2009)	7.2***	Europe 1992-2003	1 month	Portfolio invests in companies with takeover likeliness in the highest decile with monthly rebalancing between 1995 and 2003.
Cremers et al. (2009)	9.7%*** / 15.3%***	USA 1981-2004	12 months	Rolling 10-year window model between 1991 and 2004 long on the quintile/decile of firms with highest takeover risk and short on the quintile/decile of firms with lowest takeover risk.
Ouzounis et al. (2009)	4.8%***	UK 2001-2006	12 months	Portfolio constructed at the beginning of 2006 based on a forecast combination model.
Rodrigues et al. (2013)	4.0%***	AUS 1999-2011	12 months	Portfolios constructed yearly at the end of June in 2009, 2010, and 2011 using forecasts from a combination of logistic and neural network models.
Danbolt et al. (2016)	11.4%**	UK 1988-2011	12 months	Portfolio constructed yearly at the beginning of July between 1996 and 2011.

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

2.2 Discussion on previous literature

Based on our literature review, we argue that existing research on takeover prediction could benefit from improvement in the following areas.

First, most previous literature employs bi-yearly or yearly models. In other words, the models seek to predict PTOs occurring a year or half-a-year from the time of prediction. In essence, this causes the models to be inherently bad at timing, as in a yearly specification the time to PTO can be anything between 1 day and 12 months. Of the papers we study only Brar et al. (2009) employ a monthly specification. Interestingly they conclude that abnormal returns can be generated with a PTO prediction strategy. Thus, altering models to monthly specifications could yield better results. Furthermore, most studies employ small datasets, not representative of the whole stock universe, rendering results less realistic. Our study thus seeks to include all available non-PTO and PTO firm-months as explained in Section 4, Data construction.

Second, it seems that after the introduction of logit regressions in PTO prediction, they have become the dominant methodology for modelling takeover likelihood. Nonetheless, a limited number of studies have explored more sophisticated prediction methods, yielding promising results. For instance, Ouzounis et al. (2009) and Rodrigues and Stevenson (2013) employ alternative modelling techniques and are able to generate abnormal returns. Their papers, however, employ a very short time period and a small dataset, which might impact the results. Furthermore, in recent years, the availability of advanced machine learning models has increased, making them more accessible and perhaps more capable than the models used by the abovementioned studies. Hence, in this study, we explore more sophisticated classification techniques, as explained further in Section 3.

Third, only a few new hypotheses have been introduced in a takeover prediction setting in the past two decades or so. The hypotheses introduced by Palepu (1986) are largely still used in later studies, even up to the latest papers. New hypotheses or variables are introduced only seldom, and their impacts on predictive ability are hard to address due to different samples and settings. It is, however, evident that introducing new variables can play a key role in model improvement. Yet, the discussion on which variables work the best is likely dependent on the sample, making the selection cumbersome.

Fourth, explanatory variables are often simple in comparison to other fields of finance literature. For instance, most variables are elementary accounting-based variables such as sales growth or cash to all capital and include little adjustments to enhance comparability. Thus, to improve prediction and decrease timing issues, we look for alternative, perhaps more advanced, variables from other areas of finance research.

Fifth, only simple screens have been used to mitigate issues related to distressed companies being misclassified as targets. To bring more depth into the analysis, we draw inspiration from the bankruptcy literature. Section 5, Variable formulation, explores the use of alternative hypotheses and variables as well as the incorporation of more developed measures of risk and distress used to distinguish between PTO targets and distressed firms.

3. Forecasting strategies

This section describes the modelling techniques used for forecasting takeovers in our study. As highlighted above, logit models have been dominantly used for modelling takeover likelihood in previous studies. Fewer studies have explored the use of alternative, more advanced modelling techniques. As the aim of our research is to mitigate issues that often negatively impact returns of takeover prediction models, we test alternative techniques that to our knowledge have not been used in the field before.

In addition to using a logit model for benchmarking our performance, we employ two alternative machine learning models to assess the likelihood of corporate takeovers: random forest and gradient boosting. Each model is ideally suited for the standard classification problem presented by takeover prediction. Both advanced models, which are at the core of modern machine learning, offer robust, ready-to-use solutions. Unlike logistic regression, neither random forest nor gradient boosting assumes a linear relationship between the features and the dependent variable, likely enhancing their predictive capability in this context. Furthermore, both models utilize multiple independent weak learners in forming a prediction, likely decreasing the risk of overfitting. Recognizing the unique advantages and limitations of each approach, we integrate their outputs in a forecast combination to create a more accurate and reliable prediction. Whilst there are many ways to combine the different classification techniques, we apply a simple average approach, effectively giving each model equal weight in the combined forecast.

We adopt a binomial framework to model takeover likelihood for all three modelling techniques. Previous literature (e.g., Brar et al., 2009; Cremers et al., 2009; Danbolt et al., 2016; Palepu, 1986; Tunyi, 2019) favour both binominal and multinominal approaches (e.g., De Jong & Fliers, 2020; Meghouar & Ibrahimi, 2020; Powell, 2004). A binominal framework is preferred within our study due to the futility of labelling different categories of bids ex-post (e.g., friendly or hostile). Most bids receive their labels after the announcement, making the categorization trivial for us as the returns that we are trying to catch have already been realized at this point. Also, the categories would be unevenly weighted, which in turn would increase the risk of overfitting in our models.

Before training the models, all independent variables are standardized to zero mean and unit variance to make them suitable for regularization. Furthermore, all models are trained with balanced weights to mitigate issues born from the uneven distribution of PTO and non-

PTO firm-months. Finally, we predict PTOs in month $t+1$ with variables known at the end of month t. The models are trained on data trailing month t by 10 years[1].

3.1 Logit classification

In the benchmark logit model, we assume that the marginal probability of a PTO occurring next month follows a logistic distribution and is given by:

$$P_{t-1}(Y_{it}=1)=\frac{1}{1+\exp\left(-\alpha-\beta x_{i,t-1}\right)}.$$

We use *sklearn's LogisticRegressionCV* with ridge-regularization and balanced weights to run the estimates. The level of regularization is determined using stratified K-folds with the objective of maximizing the model's F1 score[2].

3.2 Random forest classification

As an alternative to the logit model, we utilize a random forest approach. In essence, random forest employs a combination of random decision trees each trained on a subset of data to improve the model's overall performance and accuracy. Each subset is formed with bootstrapping, meaning that data points selected to a subset are returned to the sampling population and thus may be selected multiple times for the same subset. Each decision tree then makes a prediction (votes) for a class and the class is labeled based on the majority rule. All in all, the use of the random forest is favored in our study due to it being especially robust to overfitting, and data with possible multicollinearity. Furthermore, random forests can handle complex, non-linear data relationships as they do not assume a linear relationship between the features and the dependent variable: a key strength in comparison to a logit model. In our study, we use Balanced*RandomForestClassifier* from *imblearn* with default specifications to run the random forest models.

3.3 Gradient boosting classification

As an alternative to the logistic regression model, we consider the gradient-boosting approach. Gradient boosting is similar to random forest in that it uses a group of decision trees to make predictions. However, gradient boosting improves on this by sequentially adding new models on top of old models to correct the errors made by previous models. This "boosting" is done using gradient descent, which effectively minimizes the errors or

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[1] See Figure A2 in the Appendix for more details

[2] F1 score is the harmonic mean of precision and recall. It measures how well a model can classify events.

differences between the predicted and actual outcomes. Furthermore, unlike simple random forests, which employ bootstrapping, gradient boosting uses a more sophisticated method of sampling and weighing the data points based on previous errors, enhancing its effectiveness. We choose gradient boosting for our study as it efficiently handles large datasets, offers built-in mechanisms to prevent overfitting, and can deal with feature interactions and non-linear relationships. We utilize *XGBClassifier from* xgboost with default specifications to run the models. Before training the model, we balance the weights of PTO months and non-PTO months using *sklearn's compute_class_weight* function.

3.4 Forecast combination

To mitigate any model-specific biases, we create a forecast combination technique by simply averaging the predicted probabilities of each technique per observation. Thus, our forecast combination model is given by:

$$P(PTO)_{Forecast\ combination} = \frac{P(PTO)_{Logit} + P(PTO)_{Random\ forest} + P(PTO)_{Gradient\ boosting}}{3}.$$

We hypothesize our prediction accuracy to increase by combining the different forecasting techniques, as the techniques most likely supplement each other in areas where a single technique could fall short. For instance, Ouzounis et al. (2009) and Rodrigues and Stevenson (2013) find that a forecast combination method surpasses individual models in performance and should be utilized to enhance the accuracy of takeover target predictions (papers use UK and Australian data).

4. Data construction

In this section, we provide an explanation of the data sources utilized in our study. Overall, our panel dataset for predicting PTOs has a frequency of one month and includes all companies listed in the US between 1994 and 2023, with the exception of financials (SIC code 6000-6999), regulated utilities (SIC code 4900-4999), and companies categorized as public service, international affairs, or non-operating establishments (SIC code > 9000). The exclusion of certain industries is consistent with a vast body of literature[1] and is done to avoid issues related to unique reporting standards, which render the interpretation of financial ratios different.

The independent variables are built on accounting data from COMPUSTAT, market data from CRSP, and mergers and acquisitions data from LSEG Deals Screener. Additionally, we utilize public sources, such as the Federal Reserve Bank of St. Louis, to retrieve data on US treasuries, consumer price inflation, and market indexes. The dependent variable is built on PTO data from LSEG Deals Screener – firm-months with PTOs are labelled as ones, and firm-months without PTOs are labelled as zeros. As we aim to forecast takeovers one month in advance, data for the independent variables is lagged by one month. For example, a PTO occurring in month t is combined with independent variables from month $t - 1$[2]. We require firm-months included in the dataset to have complete data availability for all variables. Our final dataset includes a total of 1,091,272 firm-months, of which 4,297 are firm-months with PTO bids.

4.1. Data for independent variables

First, we lag the accounting data from COMPUSTAT by two months from the fiscal period's ending date to ensure that the data is available to all investors, thus, mitigating issues related to any look-ahead bias following Campbell et al. (2008)[2]. In the case of multiple accounting data observations per firm and fiscal period, we use the one with the latest data date. As we forecast with a frequency of one month, we resample the quarterly accounting data to monthly observations. Resampling is done by forward filling a quarterly observation by two months.

The accounting data from COMPUSTAT is then merged with CRSP data via the CRSP-COMPUSTAT linking table based on PERMCOs and GVKEYs, considering the linking periods

[1] See for instance Danbolt et al., (2016), Deshmukh, (2003), Tunyi, (2019) and Ahn et al., (2006)

[2] See Figure A2 in the Appendix for illustration

for each connection. In the case of multiple existing connections for the same PERMCO and month, we use the one with the latest expiration date. We use only LC and LU links when merging data. In the case of multiple PERMNOs for one PERMCO, we use total returns of the PERMNO with the highest average split-adjusted trading volume. Market capitalizations for PERMCOs with multiple PERMNOs are calculated as the sum of PERMNO-level market capitalizations per observation date. After merging the data from COMPUSTAT and CRSP, we add the industry-specific M&A data and general macro indicators to the dataset based on SIC-codes and dates, depending on the type of connection.

4.2. Data for the dependent variable

We start by identifying all mergers and acquisitions between 1994 and 2023 from LSEG Deals Screener in which the target of the acquisition is a publicly traded entity listed in any stock exchange in the United States and the deal has a disclosed dollar value. We focus on takeover bids, and thus, also bids that eventually fail are included in the dataset. Lastly, we filter out any bids which, even if completed, would not result in the bidder gaining control.[1] Our initial list includes 15,339 PTOs.

Consequently, we are only interested in modelling the occurrence of an initial bid, not the occurrence of any subsequent bids or bidding wars. This reflects our ambition of trying to find companies that in general could receive a PTO bid. We do not want to give companies experiencing bidding wars any extra weight. Therefore, a bid is only included in the list if no bids have been published for the same target entity in the past 365 days. In other words, we assume that a bid with a gap of one year to the previous bid is part of a new bidding process. A similar approach has been utilized by e.g., Dimopoulos & Sacchetto (2014) in their study of takeover contests. Furthermore, a timeframe of 365 days is supported by Eckbo et al. (2020) who find that hardly any bid contests last over 260 days from initiation to closing. After filtering bids based on the timing rule, we are left with 14,246 PTOs.

We continue by matching the PTOs with their corresponding stock returns from CRSP. To calculate the returns for the bids, we merge PERMCOs with the dataset based on WRDS' COMPUSTAT-CRSP linking table and the PTOs' 6-digit CUSIPs, considering the linking periods for each connection. In the case of multiple existing connections for the same PERMCO and month, we use the one with the latest expiration date. We use only LC and LU links when merging data. We found PERMCOs for 6,588 PTOs.

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[1] Initial target sample selection is done in line with prior studies, e.g., Dimopoulos & Sacchetto (2014) and Danbolt et al., (2016), & Ambrose and Megginson (1992)

To limit the sample to PTOs with an initial positive price reaction, we filter out any PTO bids that do not achieve a cumulative abnormal return of zero percent or more within the announcement date and two trading days after the announcement date. This is done on the notion that we are only interested in predicting positive price reactions, as this is a prerequisite for generating abnormal returns in later portfolio formulation. PTOs in our dataset could have negative announcement returns if, for example, a PTO is misidentified in LSEG Deals Screener, or a bid would have been triggered by a distress event, such as in the case of the merger between UBS and Credit Suisse (Illien, 2023). As the market return, we utilize the S&P500 with assumed market-wide betas of 1. After filtering PTOs on abnormal returns, we are left with 5,278 unique targets.

Finally, we merge the PTOs with our set of independent variables (including only firm-months with complete data for all variables) leaving us with a total of 4,297 PTOs. We label all PTO firm-months with ones and non-PTO firm-months with zeros. In our model, we are only interested in forecasting PTOs at the end of the month preceding the bid announcement. Thus, the following 11 months after a bid is announced are dropped from the dataset, aligned with our timing rule of one year. This way, we won't confuse our model with zeros or ones on PTOs that have already taken place, likely enhancing the model's timing capabilities.

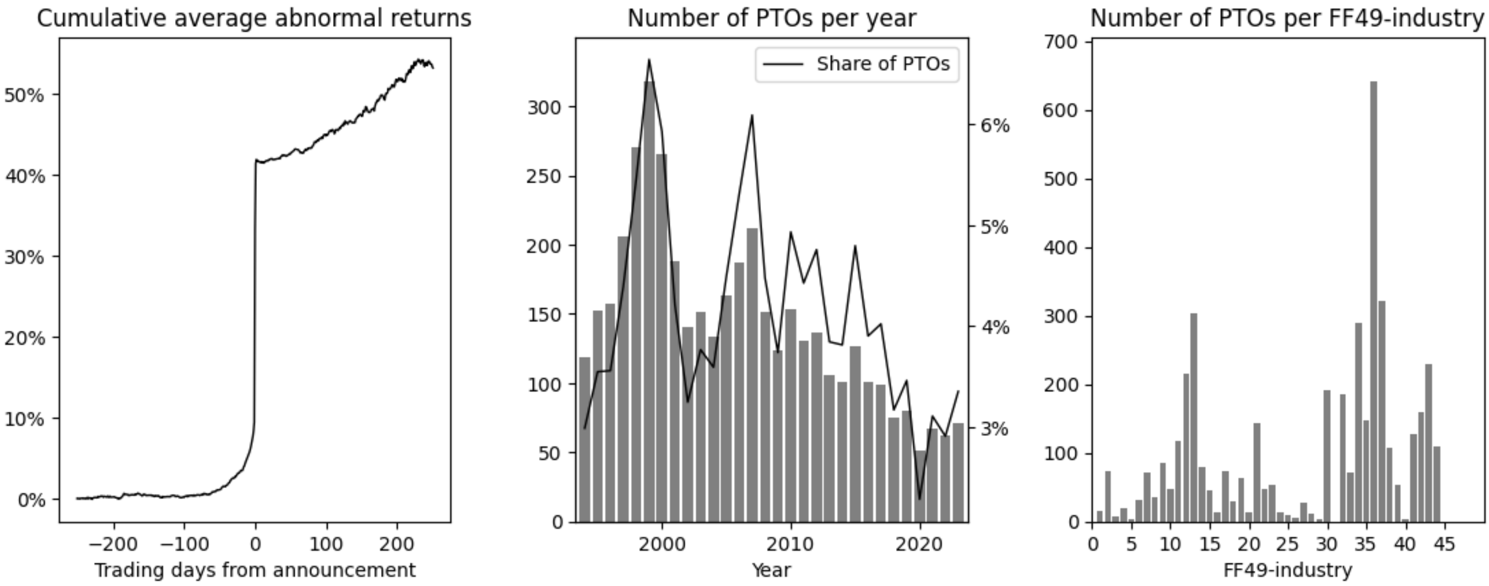
The 4,297 PTOs included in the model have, on average, cumulative abnormal returns of ~40% around the announcement date. Most PTOs occur in the software industry when categorized on the Fama-French 49 industries. As expected, the cyclical nature of mergers and acquisitions can be seen in our PTO dataset with peaks both before the Dotcom bubble and the great financial crisis. In general, the number of PTOs has been decreasing since the 90s.

4.3. Data adjustments

When calculating the independent variables, we eliminate outliers from financial ratios by winsorising at the 1st and 99th percentiles. Moreover, we modify total assets following Campbell et al. (2008) to account for possible faults in the data. To account for book values that are small and most likely faulty, we adjust total assets by adding 10% of the difference between market and book equity to the book value of total assets.

Figure 1 – PTO characteristics

The figures show the general characteristics of the 4,297 PTOs included in the study. The first figure shows the cumulative average abnormal returns of PTOs around the announcement date, the second figure shows the number of PTOs and their share to all companies included in the study per year, and the last figure shows the distribution of PTOs by Fama-French 49 industries.



5. Variable formulation

This section describes the models and variables used for forecasting PTO targets in this study. We start by building a base model following Danbolt et al. (2016). We then build an enhanced model on top of the base model. This is done by replacing some existing variables with more sophisticated ones and by introducing additional hypotheses related to firm risk and timing. After introducing the alternative variables, we analyse how they co-exist with the variables of the base model. We then drop any base model variables deemed to correlate too extensively with a new variable. In Section 6, we continue by employing the models to predict PTO targets and form an investment strategy based on our predictions.

5.1 Base model

A set of time-varying, market, industry, and firm-specific characteristics is employed for the prediction of potential takeover targets. Drawing inspiration from Danbolt et al. (2016), we develop a base model founded on eight widely recognized hypotheses. Five of these were initially proposed by Palepu (1986), namely: *firm misvaluation, inefficient management, industry disturbance, firm size, and growth-resource mismatch.* Consistent with e.g., Powell (1997) and Ambrose and Megginson (1992) *free cash flow* and *tangible assets* are also included. Furthermore, we incorporate the concept of *firm age*, consistent with e.g., Agarwal and Gort (2002). Hypotheses in the base model are as follows:

Firm misvaluation: Firms that are misvalued are likelier targets.

The firm misvaluation hypothesis suggests that "cheap" firms are likelier to get acquired. An acquirer can capture this undervaluation either by acquiring undervalued assets (compared to fundamental value) with cash or by using equity to pay for targets that are less overvalued than that of the bidder's stock (Cremers et al., 2009; Dong et al., 2006; Palepu, 1986).

Following e.g., Danbolt et al. (2016) and Cremers et al. (2009) an indicator (TQ) similar to Tobin's Q is used as the variable for misvaluation as inspired by Hasbrouck (1984). TQ is estimated as the sum of the book value of debt (i.e., the difference between the book value of assets and the book value of equity) and the market value of equity, scaled by the book value of assets. As per previous research, although Tobin's Q originally employs asset replacement costs, we use ordinary book values due to lack of replacement cost data.

Inefficient management: Firms with underperforming management are likelier targets.

The hypothesis is motivated by the notion that takeovers may be motivated by the opportunity to eliminate wasteful behaviour of the target firm, e.g., replace underperforming management (Dong et al., 2006; Palepu, 1986). Following, e.g., Cremers et al. (2009) and Danbolt et al. (2016) we use average excess returns (AER) and firm profitability to capture management performance. AER is defined as a firm's average monthly return over the market (S&P500) during the past trailing 12 months. We proxy firm profitability with NITA, which is defined as the trailing 12 months' net income scaled by the book value of total assets at the beginning of the trailing 12 months. Strong empirical evidence has been found to support the impact of AER on takeover likelihood (Cremers et al., 2009; Danbolt et al., 2016; Powell & Yawson, 2007), however, limited proof has been found to support profitability measures. Previous literature has often used ROCE, ROE, or ROA as a proxy for firm profitability, but as their explanatory power has been found marginal we utilize NITA, which has been favoured in other streams of literature (e.g., Campbell et al. (2008)).

A clear distinction must be made between *inefficient management* and *misvaluation* as the former builds upon assets not being utilized efficiently and the latter from the asset being misvalued in its current state. Making a distinction between the two with accounting and market-based figures is, however, difficult as both could drive chosen proxies: high market value can be taken as a proxy that a firm is well run or has ample prospective opportunities (Dong et al., 2006). We, however, follow previous literature in grouping these proxies under two distinct hypotheses.

Industry disturbance: Firms operating in industries with "economic disturbances" are more likely to get acquired.

This hypothesis originates from Gort (1969) who argues that mergers are driven by changes in valuation among market participants, which are precipitated by economic disturbances, including shifts in technology, industry structure, and the regulatory landscape. Gort also argues that acquisitions cluster by industry, and thus in line with previous literature, we create an M&A indicator (M&A) to proxy disturbance. Empirical support for this hypothesis has been found by i.e., Palepu (1986) and Cremers et al. (2009).

In our study, M&A is defined as the sum of the number of mergers and acquisitions taking place in the firm's 4-digit SIC industry in the trailing 12 months. The deals are identified from LSEG's Deals Screener. The indicator includes all completed deals where the target is headquartered in the United States and the deal results in the acquirer gaining control over the target. Most studies have used a dummy for industry disturbance, but in our larger sample nearly all industries would always receive the same dummy value.

Firm size: Small and medium-sized firms are likelier takeover targets.

The original theory, as put by Palepu (1986), suggests that the likelihood of acquisition decreases with the size of the firm. Previous literature, however, fails to conclude this is the case with the latest literature indicating that mid-sized companies are most at risk for takeovers (Tunyi, 2019). We thus hypothesize that small and medium-sized firms are likelier targets with large companies experiencing less takeover threat. Consistent with e.g., Tunyi (2019) and Danbolt et al. (2016) we use the natural log of total assets as a proxy for target firm size (SIZE).

The reasoning behind the original theory is that acquiring a target involves various transaction costs related to size, which means that as the size of the target increases, the pool of potential acquirers decreases. These expenses encompass the market price plus an acquisition premium for the target, fees associated with mergers, and acquisition negotiations. Tunyi (2019), however, argues that although acquiring small firms may be financially manageable, such acquisitions might not enable acquirers to fully achieve various well-documented takeover motivations, including economies of scale, managerial overconfidence, market dominance, and aspirations for empire expansion.

Growth-resource mismatch: Firms with a mismatch between their growth and available financial resources are likelier targets.

This hypothesis suggests that firms with a mismatch between their growth and financial resources at their disposal are likely targets (Palepu, 1986). For instance, companies experiencing rapid growth but suffering from a lack of resources (such as low cash reserves and high debt) might attract acquisition interest from companies with the reverse situation – those with slow growth but abundant resources. Similarly, companies with slow growth but substantial resources could be appealing to fast-growing companies that are resource-constrained, aiming to capitalize on the target company's surplus cash flows. By merging with a company that has a contrasting growth-resource profile, the overall value of the newly formed entity is anticipated to surpass the sum of the individual values of both companies involved (Powell, 1997). Empirical support for this hypothesis has been shown by among others, Powell (2004) and Palepu (1986). We do not form a hypothesis on the direction of sales growth, liquidity, or leverage as the growth-resource mismatch itself allows for both directions.

Consistent with previous literature (e.g., Palepu, 1986; Tunyi, 2019), we proxy the growth-resource imbalance with four firm variables: growth (SG), liquidity (LIQ), leverage (LEV), and a growth-resource dummy (GRD). We define sales growth as the relative difference between a firm's sales in the trailing 12 and 12-to-24 months, liquidity as cash and short-term investments to total assets, and leverage as total liabilities to total assets. GRD takes a value of one when (1) a firm has high sales growth combined with low liquidity and high leverage, or (2) when a firm has low sales growth combined with high liquidity and low leverage, and a value of zero in all other cases (Danbolt et al., 2016). A variable is defined as "low" or "high" by comparing individual values with the Fama-French 49-industry medians, slightly differing from previous literature which has favoured the use of average values as the proxy for "high" and "low".

Free cash flow: Firms with high free cash flow are likelier targets.

This hypothesis is grounded upon the notion of corporate takeover theory that suggests that companies that accumulate free cash flows rather than benefit their shareholders (via e.g., dividends) end up creating an agency problem which creates opportunities for potential acquirers to solve. Extending this theory, the issue becomes increasingly difficult the more free cash flow a firm generates (Jensen, 1986; Meghouar & Ibrahimi, 2020). This hypothesis is further backed by the notion that appealing acquisition targets for buyouts are often financed with high leverage, for which free cash flows are desirable (Jensen, 1986). Empirical support for this hypothesis has been recorded by among others Danbolt et al. (2016), Meghouar and Ibrahimi (2020), and Palepu (1986). Inspired by e.g., Danbolt et al. (2016), free cash flow (FCF) is the ratio of free cash flow to equity from the trailing 12 months scaled by total assets at the beginning of the trailing 12 months. Free cash flow in itself is calculated as net cash flow from operating activities subtracted by capital expenditures. If net cash flow from operating activities is unavailable, we proxy free cash flow as the sum of net income and depreciation subtracted by the sum of working capital changes and capital expenditures.

Tangible assets: Firms with substantial tangible assets are likelier targets.

This hypothesis suggests that firms with a substantial proportion of tangible fixed assets (PPE) in their asset structure are likelier targets as shown first by Ambrose and Megginson

(1992). The relationship between tangible assets and takeover likelihood could be the result of tangible assets acting as a proxy for greater debt capacity (Johnson & Stulz, 1985). Furthermore, the acquiring party could in theory use the target's assets as security for any debt financing, possibly lowering the cost of the acquisition, and thus making such a target more desirable (Powell, 2004). Consistent with prior studies (e.g., Ambrose & Megginson, 1992; Danbolt et al., 2016; Powell, 2004) the ratio of property, plant, and equipment to total assets is used as a measure for tangible assets (TANG).

Firm age: Older firms are less likely targets.

The hypothesis predicts that older firms are less likely takeover targets as found by i.e. Tunyi (2019) and Danbolt et al. (2016). This is based on the notion that firm endowments and the general tendency of firms learning by doing, in other words, through time (Agarwal & Gort 2002). For instance, Agarwal and Gort (2002) argue that as time progresses, a firm accumulates knowledge regarding its own operations and its industry. Also, this accumulated knowledge enables the firm to lower costs, enhance products, and innovate new market strategies. Initially, firms start with limited resources, but these resources grow over time as the firms invest in research and development, making them less likely takeover targets. Firm age (AGE) is measured as the number of years since its listing on an exchange consistent with e.g., Shumway (2001). Years since listing is calculated based on the first monthly return observation in CRSP.

5.2 Enhanced model

In this section, we explain the augmentations performed to the base model to form the enhanced model. As outlined in the introduction we aim to 1) decrease prediction errors, 2) enhance timing and 3) reduce issues related to misclassifying bankrupt firms as potential targets. To do so we investigate asset pricing literature to identify potential ways to minimize the aforementioned issues.

Firstly, we identify that Asness et al. (2018) derive alternative, perhaps more accurate, ways of proxying financial aspects of a firm in their paper "Quality minus Junk". Secondly, we turn to distress literature in search of an effective way of reducing the misclassification of distressed entities as targets. We identify Distance to default (DD) as an effective and viable way of measuring distress in this context. We then form a new hypothesis called *firm risk* which combines the Safety measure of Asness et al. (2018) and Distance to default. Thirdly, we adopt technical measures related to firm stock price momentum, trading volume, and overall equity market sentiment to address issues associated with timing accuracy. Please see Table 4 for an overview of the base and enhanced model. We first introduce the alternative variables and then analyse how they co-exist with the variables of the base model. We then exclude any base model variable deemed to correlate too extensively with an enhanced model variable.

5.2.1 Applying Quality for takeover prediction

Asness et al. (2018) define Quality as "Characteristics that investors should be willing to pay a higher price for, everything else equal" (Asness et al., 2018, p. 35) or more specifically, a function of three characteristics: Profitability, Growth, and Safety. They also include a measure of Payout in their analysis. In essence, Asness et al. (2018) find that investors pay more for Quality, however, not enough to completely price in Quality, resulting in high-Quality stocks being able to deliver high risk-adjusted returns. Asness et al. (2018) suggest that market prices fail to fully price in such Quality characteristics due to reasons possibly related to behavioral finance or constraints.

To build their Quality minus Junk (QMJ) factor they first measure a firm's performance in terms of Profitability, Growth, and Safety after which the characteristics are combined to form the overall QMJ factor. Each characteristic is formed as a composite of various empirical measures. For instance, Profitability is formed equally on gross profits over assets, return on equity, return on assets, cash flow over assets, gross margin, and low accruals.

This approach opens vast opportunities for takeover prediction. Firstly, we can use these three components of QMJ and the additional Payout component to more accurately proxy our base hypothesis described above in Section 5.1. Secondly, Quality might be a factor that affects PTO likeliness in itself. This is based on the suggestion that market prices do not fully account for such Quality characteristics, possibly due to factors related to behavioral finance or constraints. If the market fails to price in Quality, acquiring Quality firms should result in better deals and higher returns, possibly making Quality firms likelier PTO targets. Hence, if the market does not accurately price in Quality, acquisitions of such entities may be driven by more sophisticated parties who are less affected by behavioral biases or financial constraints. These parties are likely able to time their acquisitions to periods when the price of Quality is relatively low.

Such timing behavior is made possible by the notion that the price of Quality tends to decrease in favorable economic conditions and increase in times of less so. For instance, the price of Quality reached its lowest value during the internet bubble and highest after the Enron and WorldCom scandals in 2002. This pattern is clearly visible when plotting the trailing 12-month average PTO count with the trailing 12-month average QMJ returns of the same period (see Appendix Figure A1). Hence, the importance of the Quality factor could increase as high deal-making activity is most likely to coincide with times of low price of Quality. In other words, when deal-making activity is more favorable, Quality firms are better buys, which could increase the attractivity of high-Quality firms as PTO targets.

In essence, the subcategories Profitability and Growth are a much more comprehensive way of proxying the *inefficient management* hypothesis, which in the base model is measured with net income over assets (NITA) and average excess returns (AER). Furthermore, the subcategory Payout suits the *free cash flow* hypothesis as it measures the amount that is actually paid out to shareholders also considering share issuance. Finally, the subcategory Safety is included under a new hypothesis *Firm risk* which is discussed in the next Section 5.2.2. In essence, we hypothesize that different levels of firm risk impact the likeliness of takeover.

As the methodology employed by Asness et al. (2018) contains various detailed steps, we only include a concise description of the calculations in our paper as well as a list of components on each subcomponent in Table 2. Each Quality characteristic (Profitability, Growth, Safety, Payout) contains several empirical measures such as ROA, Z-Score, and beta. To standardize and integrate each measure on an equal basis, they transform each variable monthly into rankings and then standardize each ranking to obtain a z-score. Finally, they calculate composite z-scores of the variable-level z-scores to proxy the Quality characteristics.

We slightly alter the methodology used by Asness et al. (2018) to better suit our purpose by calculating each variable on a rolling 12-month basis rather than yearly, and by calculating all Growth variables such as growth in gross margin based on yearly change rather than five-year change. Furthermore, we fill any missing values with their cross-sectional means before standardizing, winsorise all variables except betas in the 1st and 99th percentile, and give equal ranks to identical values. The adjustments are made to ensure better data availability and to account for potential outliers.

Although the standardization methodology differs significantly from the raw measures used as proxies in our base model, the base variables and Quality components could still have a high correlation due to their thematic similarity. To avoid such issues when forming our enhanced model, we test the variables for correlation and retain only distinctive features, as explained later in Section 5.2.4. In short, to alleviate any issues born from multicollinearity and overlap between the variables, we decide to drop NITA, LEV, and FCF from the enhanced model and replace them with more holistic PROF, GROW, and SAF measures.

Table 2 – Subcomponents of Quality by Asness et al. (2018)

This table represents the subcomponents used to form the Quality minus Junk (QMJ) factor by Asness et al. (2018). In our study each subcomponent is used as a predictive variable. In the formation of a subcomponent each indicator receives equal weights.

Profitability	Growth	Safety	Payout
Gross profits over assets	In residual return on equity	Leverage	Net equity issuance
Return on equity	In residual return over assets	Beta (BAB)	Net debt issuance
Return on assets	In residual return in CF over assets	Ohlson's O	Net payout over profits
Cash flow over assets	In residual gross profit over assets	Altman's Z	
Accruals	In gross margin	Earnings volatility	
Gross margin			

5.2.2 Firm risk

We hypothesize that firms with higher risk profiles are more likely to become targets for PTOs, provided they are not experiencing immediate distress. In our study, firm risk is defined as the likeliness of a firm to experience extreme negative outcomes (downside risk), all other things equal. Should our hypothesis prove inaccurate, we posit that incorporating a more granular[1] measure of firm risk into the model will nonetheless enhance the predictive performance.

Previous research has identified that takeover targets often have higher debt-to-equity ratios, lower liquidity, and exhibit generally poorer performance. Hence, PTO targets are suggested to share similar characteristics with distressed firms. This has led to target portfolios being prone to underperformance due to a disproportionately high number of distressed firms being misclassified as potential targets. (Brar et al., 2009; Cremers et al., 2009; Danbolt et al., 2016; Powell & Yawson, 2007) In other words, takeover models are not able to fully distinguish between PTO targets and distressed companies. Extending on these findings, we hypothesize that firms with higher risk profiles are more likely to become targets for PTOs, provided they are not experiencing immediate distress. Our aim is to not only leave out distressed firms from target portfolios, but to also enhance our model's ability to identify between the riskiness of non-targets and targets, which could increase model performance.

[1] As opposed to measures of leverage and liquidity

But why would PTO targets resemble distressed entities? This question has been left widely unanswered in existing literature even when it has largely concluded that this is the case. One possible explanation is *inefficient management*, which could perhaps manifest in various other forms as well, including higher earnings volatility, higher beta, and increased debt levels. Hence, such characteristics, which we group under *firm risk* might cause a disciplinary check on managerial performance and provide opportunities for acquirers to fix. Also, in firms with the highest levels of risk, poor-performing management might use a liquidation event to transfer their assets to higher-valued uses. (Shrieves & Stevens, 1979; Sullivan et al., 1997) Hence, seeking to exit via a public takeover might also be a way of avoiding bankruptcy. Once in actual default, such actions can no longer be undertaken.

Furthermore, the fact that PTO targets resemble distressed entities may be connected to buyer characteristics and their underlying motivations. For example, buyouts often target turnaround scenarios where the company is experiencing difficulties (Cohn et al., 2022). Such poor performance can manifest in various forms, such as general undervaluation, low profitability, or elevated levels of risk stemming from higher debt levels or earnings volatility. The root causes of these issues are potential sources of value creation for buyouts. Hence, it can be that companies with increased risk (resembling distressed assets) fall in the scope of buyout firms due to their potential for desired return profiles and value creation opportunities that such buyers seek.

Previously, two studies, namely Powell and Yawson (2007) and Danbolt et al. (2016) have studied strategies for mitigating this issue. Powell and Yawson (2007) run a multinominal approach in which they also include divestitures, layoffs, and bankruptcies into the model. In other words, they run a model that seeks to explain four different restructuring events, hence allowing the model to differentiate between them. Doing so reduces misclassification but does not completely solve the issue. Further, Danbolt et al. (2016) employ a set of screens based on the Taffler Z-Score[1], size, leverage, and liquidity to identify distressed firms ex-ante and exclude them from portfolios built on takeover likelihood. All in all, Danbolt et al. (2016) find that such screens can substantially improve portfolio returns, even to such an extent that they are able to generate abnormal returns of 0.9% per month (in a CAPM framework). These studies, however, do not seek to differentiate between the riskiness of non-targets and targets.

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[1] Taffler, R.J. (1983) The Assessment of Company Solvency and Performance Using a Statistical Model: A Comparative UK Based Study. Accounting and Business Research, 13, 295-307. https://doi.org/10.1080/00014788.1983.9729767

Fine-tuning between PTO targets and distress is a tricky issue: should we exclude also firms that are somewhat distressed but still able to continue as a going concern, we are likely to exclude many viable takeover targets from our portfolios: taking distress into account does not change the fact that many PTO targets are in fact companies that resemble distressed entities. As the previous methodologies have still left areas to improve on this front, we look into distress literature for possible alternative ways to mitigate the issue and consequently propose a framework for distinguishing between the riskiness of distressed assets and PTO targets.

We identify that *firm risk* could be measured with two variables: one that identifies severe cases of distress and one that looks at *firm risk* more comprehensively also in going concern states. Doing so we expect to be able to identify severe cases of distress, which are likely not PTO targets, and differentiate between the riskiness of firms that operate as going concern, enhancing the model's predictive ability. In our framework Distance to default (DD) (Bharath & Shumway, 2008) is used to proxy for severe cases of risk and Safety (SAF) ((Asness et al., 2018) for risk in going concern states.

Distance to default is selected for our severe distress screen as it has been found to be highly effective and robust[1] in forecasting corporate failure (see Campbell et al. (2008) and Bharath and Shumway (2008)). Furthermore, DD is highly spread out to the tails, thus making it a great fit for identifying firms that are very close to bankruptcy. To differentiate between other levels of risk we utilize the Safety measure of Asness et al. (2018). Safety is derived from the subcomponents of beta, leverage, low bankruptcy risk (Ohlson's O and Altman's Z), and earnings volatility. Even though Ohlson's O and Altman's Z are similar to that of DD, they are inherently different in their ability to measure risk at the tails of the distribution. Looking at the summary statistics, we find only a -29% absolute correlation between the two, thus highlighting their difference. For clarity, a lower DD and a higher Safety imply lower risk in our framework.

As deriving DD contains various detailed steps, we only include a concise description of the methodology in our paper. We follow Campbell et al. (2008) in calculating the DD measure. In essence, we estimate the difference between the asset value of a firm and the face value of a firm's debt, scaled by the standard deviation of the asset value. As both the asset value of a firm and its standard deviation are not directly observable, we estimate them by solving

[1] Compared to Altman's Z-score and Ohlson's O-score. DD is also seen as a robust alternative for dynamic logit models introduced by Campbell et al. (2008)

a system of two nonlinear equations derived from the Merton model. Finally, we insert the value into a cumulative distribution function to get a point estimate on the probability of a firm going bankrupt during the following year.

To further mitigate the effects of distress, as previously explained, we train our models only on PTOs that receive positive announcement returns. Some takeovers might be triggered by distress events, such as the merger of Credit Suisse and UBS (Illien, 2023), which could increase the risk of misclassification. Finally, we also test whether using ex-ante screens based on Distance to default increases our portfolio returns.

5.2.3 Timing variables

To reduce timing-related issues, we include three additional variables, market sentiment, price momentum, and trading volume. Market sentiment is added to proxy market-wide timing, while price momentum and trading volume are added to proxy company-specific timing.

Market sentiment: Market conditions affect the likeliness of bid.

This hypothesis argues that even if a company would be a great bid candidate, market conditions might render a bid highly unlikely (Brar et al., 2009). In the spirit of Brar et al. (2009), we measure market sentiment (SENT) from the equity market's perspective with a dummy variable that takes a value of one if the S&P500 index had a positive total return in the trailing 12 months and zero in all other cases.

It's important to note that our specification of market sentiment does not differentiate companies in the cross-section, as it receives a single value each period based on the trailing market conditions. However, the variable has important predictive abilities when looking at the time series: if PTOs are found to be more frequent in certain market environments, all firms in the cross-section are labelled as more likely/unlikely to be acquired at any specific point in time. When using a fixed cutoff percentage based on the given probability of a PTO in making predictions, more/fewer companies are categorized to receive a takeover based on the sentiment variable. This notion is most important for analysis performed in Section 6.2.1 Overall predictive performance.

Stock market activity: Rumours, bidder activities, and insider trading increase price momentum and trading volume in the months preceding a bid.

This hypothesis predicts that the shares of targets are more actively traded and/or experience price momentum in the months prior to the announcement, as a result of speculative trading on possible takeover rumours, insider trading, or the intention of the bidder to build up a stake in the target company (toehold acquisitions). Research has extensively explored the causes of run-ups and trading volume changes, providing evidence that supports all three above-mentioned sources, varying by study (see i.e. Borges and Gairifo (2013), Gao and Oler (2011), Spyrou et al. (2010), and Tang and Xu (2016)). The price run-up can also be seen in the average cumulative abnormal returns of the PTOs included in our data, with positive returns beginning to accumulate months before the actual announcement date as shown in Figure 1.

Only a few takeover studies have employed technical measures on price, trading volume, or rumour data in general. Barnes (1998) studies anticipatory share price changes with a measure of cumulative average residual over 2 months before the bid announcement. Further, Brar et al. (2009) define price momentum as the t-statistic of a trend line slope fitted to logged stock prices, and trading volume as the average percentage of free-float market capitalisation (3 and 12 months). Brar et al. (2009) find that both price momentum and trading volume have a significant positive impact on takeover likelihood, whilst Barnes (1998) does not find anticipatory changes to improve model accuracy.

Building on the methodology outlined by Brar et al. (2009), we assess changes in trading volume (TRD) by employing a z-score. We measure the deviation of the average split-adjusted trading volume over the most recent two months from its historical average over the preceding 24 months. To compute this, we first establish a local mean and standard deviation for split-adjusted trading volumes, which are derived from the rolling average and rolling standard deviation calculated over the 24-month period. The z-score at the end of each month is then defined as: $z_{it} = (\overline{v_{t-1:t}} - \overline{v_{t-23:t}})/\sigma_{t-23:t}$. We require at least 12 periods of data for the estimation of the mean and standard deviation and both periods for the two-month window used for comparison. Finally, we fill any missing z-scores with their cross-sectional means to mitigate issues related to data availability.

We measure price momentum (PMOM) in a similar manner. First, we calculate abnormal monthly returns over the S&P500 index for each company. Then, we subtract the trailing 24-month average monthly abnormal return from the trailing 2-month average abnormal return and scale the result with the trailing 24-month abnormal returns' standard deviation to obtain a z-score. Again, we require at least 12 periods of data for the 24-month average and standard deviation, and both periods of data for the 2-month average. Finally, we fill any missing z-scores with their cross-sectional means.

5.2.4 Descriptive statistics and final model

Table 3 summarizes the properties of our 20 explanatory variables, together with highlighting their correlations and variation inflation factors. Panel A describes the distributions of the variables in firm-months without PTOs, whereas Panel B describes the distributions in firm-months with PTOs. The distributions are calculated by first averaging the monthly cross-sections, and then taking the average of the monthly averages to mitigate any time series effects. Panel C and Panel D show the independent variables' correlations and variation inflation factors for the whole data set.

The independent variables in the base model aren't significantly correlated or multicollinear. Out of the 12 independent variables, only NITA and FCF have an absolute correlation coefficient above 50%. Also, the variation inflation factors are all below or slightly above two, indicating that the model does not suffer from multicollinearity.

When comparing the base variables to our enhanced variables, cases with correlations become more frequent, however, still limited. Three variables, NITA, LEV, and FCF show an absolute correlation of over 40% with new variables PROF and SAF. This is expected, as the variables in many cases capture the same characteristics. To alleviate any issues born from multicollinearity and overlap between the variables, we decide to drop NITA, LEV, and FCF from the enhanced model and replace them with more sophisticated PROF, GROW, and SAF measures.

After dropping the variables, the enhanced model has an absolute correlation coefficient of 40% or more only in the case of PROF and SAF. Correlation between PROF and SAF is rather expected as high Profitability most likely influences Safety. Due to the assumed relationship and the fact that both variables come from the same framework, we choose to not exclude either variable from the enhanced model. Finally, all independent variables in the enhanced model have variance inflation factors well below two. Table 4 describes the base model and the final enhanced model. In the following sections, we develop models using both the base and enhanced variables as well as four different modelling techniques.

Table 3 – Summary statistics

This table shows the summary statistics of the independent variables. Panel A describes the distributions of firm-months without PTOs , whereas panel B describes the distributions of firm-months with PTOs. The distributions have been calculated by first averaging the monthly cross-sections and then taking the average of the monthly averages to mitigate any time series effects. Panel C shows the results of Welch's t-test between the two distributions. Panel D shows the correlations and panel E the variance inflation factors. See Table 4 for explanation on model variables. For the T-stat *p<0.1; **p<0.05; ***p<0.01 indicates statistical significance correspondingly.

Statistic	NITA	LEV	FCF	SG	AER	TQ	LIQ	GRD	M&A	SIZE	TANG	AGE	DD	PROF	GROW	SAF	PAY	TRD	PMOM	SENT
Panel A - Firm-months without PTOs (N = 1,086,975)																				
Mean	-2.1 %	0.46	-1.3 %	20.7 %	0.3 %	1.79	16.9 %	0.29	67	6.19	25.0 %	19	2.7 %	0.13	-0.1	0.07	0.12	0.09	-0.02	0.81
St. Dev.	2.1 %	0.03	2.1 %	9.1 %	1.4 %	0.17	2.4 %	0.02	15	0.85	1.8 %	4.5	2.7 %	0.02	0.03	0.01	0.04	0.22	0.16	0.39
Min	-9.4 %	0.42	-5.6 %	-0.2 %	-3.3 %	1.21	11.4 %	0.26	28	4.67	21.2 %	13.2	0.3 %	0.09	-0.17	0.04	0.04	-0.4	-0.46	0
Median	-1.5 %	0.45	-0.5 %	21.4 %	0.1 %	1.81	17.2 %	0.29	66	6.25	24.7 %	18	1.6 %	0.12	-0.1	0.07	0.11	0.07	-0.03	1
Max	1.3 %	0.54	2.1 %	40.0 %	4.2 %	2.22	20.6 %	0.35	100	7.48	28.8 %	27.7	17.0 %	0.18	-0.01	0.08	0.22	1.25	0.54	1
Panel B - Firm-months with PTOs (N = 4,297)																				
Mean	-2.3 %	0.47	-1.3 %	18.7 %	0.0 %	1.66	18.7 %	0.31	93	5.87	23.7 %	16	2.8 %	0.15	-0.1	0.02	0.13	0.09	0.09	0.81
St. Dev.	7.4 %	0.11	6.0 %	36.6 %	2.0 %	0.38	8.5 %	0.16	73	0.98	8.0 %	6.3	5.2 %	0.24	0.27	0.23	0.26	0.38	0.28	0.39
Min	-61.6 %	0.06	-54.4 %	-40.8 %	-7.8 %	0.72	3.7 %	0	0	3.33	0.8 %	3.5	0.0 %	-1.12	-1.16	-0.95	-1.18	-0.82	-0.81	0
Median	-0.7 %	0.46	-0.6 %	12.8 %	-0.1 %	1.63	17.7 %	0.3	72	5.76	22.8 %	15	0.6 %	0.18	-0.09	0.04	0.15	0.07	0.08	1
Max	9.7 %	0.9	12.7 %	560.7 %	8.4 %	4.66	82.9 %	1	556	8.85	54.8 %	57.6	56.6 %	1.19	1.58	0.62	1	2.25	1.03	1
Panel C - Welch's t-test between PTO and non-PTO firm-months																				
T-stat	-0.5	1.8*	-0.1	-1.0	-2.7***	-5.8***	3.9***	1.5	6.7***	-4.7***	-2.9***	-7.5***	0.2	2.0**	-0.2	-4.3***	0.6	0.0	6.8***	0.1
Panel D - Correlation matrix (N = 1,091,272)																				
NITA	100 %																			
LEV	-5 %	100 %																		
FCF	73 %	1 %	100 %																	
SG	-14 %	-9 %	-24 %	100 %																
AER	6 %	-10 %	7 %	1 %	100 %															
TQ	-13 %	-26 %	-12 %	17 %	33 %	100 %														
LIQ	-28 %	-43 %	-23 %	12 %	1 %	19 %	100 %													
GRD	-2 %	-4 %	-3 %	-4 %	-2 %	-7 %	5 %	100 %												
M&A	-8 %	-10 %	-3 %	3 %	2 %	11 %	20 %	-1 %	100 %											
SIZE	37 %	30 %	37 %	-9 %	0 %	-8 %	-26 %	-5 %	-9 %	100 %										
TANG	11 %	24 %	-3 %	-5 %	-7 %	-29 %	-39 %	-2 %	-15 %	19 %	100 %									
AGE	19 %	14 %	21 %	-14 %	-1 %	-7 %	-18 %	-2 %	-12 %	38 %	4 %	100 %								
DD	-23 %	25 %	-15 %	-1 %	-14 %	-14 %	-9 %	-2 %	-1 %	-19 %	7 %	-10 %	100 %							
PROF	70 %	-7 %	62 %	-10 %	9 %	8 %	-20 %	-3 %	4 %	27 %	0 %	13 %	-17 %	100 %						
GROW	15 %	-10 %	3 %	25 %	18 %	23 %	9 %	-5 %	4 %	-2 %	-8 %	-6 %	-6 %	28 %	100 %					
SAF	57 %	-49 %	48 %	-7 %	7 %	3 %	-2 %	0 %	-3 %	17 %	-10 %	19 %	-29 %	53 %	9 %	100 %				
PAY	22 %	4 %	29 %	-19 %	-5 %	-11 %	-8 %	-2 %	-9 %	15 %	6 %	21 %	-5 %	17 %	-2 %	24 %	100 %			
TRD	-2 %	1 %	-6 %	6 %	17 %	12 %	-4 %	-1 %	-1 %	1 %	2 %	-1 %	8 %	-1 %	7 %	-3 %	-11 %	100 %		
PMOM	-4 %	-1 %	1 %	-4 %	20 %	6 %	-1 %	0 %	0 %	-1 %	0 %	0 %	4 %	-3 %	-5 %	-1 %	5 %	6 %	100 %	
SENT	5 %	-2 %	0 %	0 %	-2 %	10 %	-4 %	0 %	-3 %	-1 %	1 %	2 %	-11 %	1 %	-2 %	0 %	1 %	4 %	-2 %	100 %
Panel E - Variance inflation factors (N = 1,091,272)																				
Base	2.11	1.46	2.11	1.09	1.14	1.27	1.57	1.02	1.09	1.39	1.34	1.14								
Enhanced				1.16	1.25	1.3	1.39	1.02	1.12	1.26	1.3	1.17	1.21	1.66	1.28	1.55	1.15	1.1	1.09	1.04

Table 4 – Model variables and hypotheses

This table describes the hypothesis and variables of the base and enhanced model. The variables for hypotheses, together with their expected signs, are shown in parentheses. A positive (negative) sign indicates that an increase in the variable increases (decreases) the likelihood of takeover. NITA is defined as the trailing 12 months' net income scaled by the book value of total assets at the beginning of the trailing 12 months. Adjusted total assets is derived by adding 10% of the difference between market and book equity to the book value of total assets. AER (average excess returns) is computed as a firm's average monthly excess return over the market (SP500) in the trailing 12 months. TQ is estimated as the sum of the book value of debt (i.e., the difference between the book value of assets and the book value of equity) and the market value of equity, scaled by the book value of assets. SG is (sales growth) is defined as the relative difference between a firm's sales in the trailing 12 and 12-to-24 months, LIQ (liquidity) as cash and short-term investments to total assets, and leverage (LEV) as total liabilities to total assets. GR dummy (GRD) takes a value of one when there is a mismatch between a firm's growth opportunities and its resources, and a value of zero otherwise. M&A is defined as the sum of the number of mergers and acquisitions taking place in the firm's 4-digit SIC industry in the trailing 12 months. Firm size is the natural log of a firm's total assets. Tangibility is the ratio of tangible assets (property, plant, and equipment) to adjusted total assets. Firm age is the number of years of share price data available on CRSP. Free cash flow (FCF) is a ratio of FCF trailing 12 months scaled by total assets at the beginning of the trailing 12 months. SENT takes a value of one if the S&P500 index had a positive total return in the trailing 12 months and zero in all other cases. PROF, GROW, PAY, and SAF are subcomponents of the Quality measure by Asness et al. (2018). Price momentum (PMOM) and trading activity (TRD) are defined as the z-score of the trading volume / abnormal return over the most recent two months from its historical average over the preceding 24 months. DD is Distance to default as per Bharath and Shumway (2008)).

		Variable (exp. sign)	
Hypotheses	**Rationale**	Base	Enhanced
Inefficient management	Firms with underperforming management are likelier targets.	NITA (-) AER (-) -	PROF (-) GROW (-) AER (-)
Firm misvaluation	Firms that are misvalued are likelier targets.	TQ (-)	TQ (-)
Growth-resource mismatch	Firms with a mismatch between their growth and available financial resources are likelier targets.	GRD (+) SG (+/-) LIQ (+/-) LEV (+/-)	GRD (+) SG (+/-) LIQ (+/-) -
Industry disturbance	Firms operating in industries with "economic disturbances" are more likely to get acquired.	M&A (+)	M&A (+)
Firm size	Small and medium-sized firms are likelier takeover targets.	SIZE (-)	SIZE (-)
Free cash flow	Firms with high free cash flow are likelier targets.	FCF (+)	PAY (-)
Tangible assets	Firms with substantial tangible assets are likelier targets.	TANG (+)	TANG (+)
Firm age	Older firms are less likely targets.	AGE (-)	AGE (-)
Firm risk	Firms with higher risk profiles are more likely to become targets for PTOs, provided they are not currently experiencing immediate distress.	- -	SAF (-) DD (+/-)
Market sentiment	Market conditions affect the likeliness of bid.	-	SENT (+)
Stock market activity	Rumors, bidder activities, and insider trading preceding takeover bid increase price momentum and trading volume in the months preceding a bid.	-	PMOM (+) TRD (+)

6. Empirical results

In this section, we begin by analyzing the characteristics of takeover targets, both by running a Welch's t-test and a logit regression between PTO and non-PTO firm-months. In consequent subsections, we run multiple predictive models, examine their robustness, and proceed with models that demonstrate the best predictive capabilities. Lastly, we formulate portfolios built on takeover likeliness and decompose the sources of these returns.

6.1 Characteristics of takeover targets

In this section, we first explore the potential discriminatory power of the independent variables by analysing differences in the means of target and non-target groups via Welch's t-test. Consequently, we analyse the variables' explanatory power in a binomial logit setting as well as differences between the base and enhanced model.

6.1.1 Univariate analysis

Table 3, Panels A and B, provide the means for each independent variable for both targets and non-targets (PTO firm-months and non-PTO firm-months), alongside Welch's t-statistics examining the differences between the means. The distributions are calculated by first averaging the monthly cross-sections and then taking their average to mitigate any time-series effects.

The results show a statistical difference between multiple means of target and non-target samples. *Firm misvaluation* receives support as TQ is found statistically smaller for targets. *Inefficient management*, on the other hand, receives only partial support. Abnormal excess returns (AER) are lower for target firms, aligned with expectations. However, of NITA and PROF, only PROF is found statistically different for targets. Interestingly, PROF is found to be higher for targets, contrary to the hypothesized direction. No statistically significant differences are found in Growth (GROW).

The *growth-resource mismatch* hypothesis receives limited evidence with the mean GR-dummy being found similar between targets and non-targets. The subcomponents of GRD – leverage (LEV), sales growth (SG), and liquidity (LIQ), however, yield surprising outcomes. The results reveal that the leverage of targeted firms is higher than that of non-targeted firms, albeit only at a 10% significance level. In addition, targeted firms exhibit similar growth compared to their counterparts. Conversely, liquidity levels are observed to be higher in targeted firms.

Firm risk receives support in the expected fashion: Safety (SAF), is found to be significantly lower for targets, while limited differences are found in terms of Distance to default (DD). The average of DD between targets and non-targets should be similar as both groups likely include some distressed entities, but most firms show very low values of Distance to default.

Evidence supporting hypotheses *firm size, firm age, and industry disturbance* is found with differences in AGE, SIZE, and M&A being statistically significant and to the direction expected. The *free cash flow* hypothesis receives limited support as both FCF and PAY are found to be similar between the two groups. *Tangibility* displays a statistically significant difference, however, to a direction opposite to that expected. *Stock market activity* receives partial support. Price momentum (PMOM) is found to differ significantly between the groups in the hypothesized direction, however, trading volume (TRD) is not found different between groups.

6.1.2 Logit regression analysis

Table 5 reports the results of the binomial logit regressions. The base model employs the 12 base variables discussed above and forms the benchmark model in our study. The enhanced model augments the set of variables with the alternative variables for the existing hypotheses as well as includes the set of timing (TRD, PMOM, SENT) and firm risk variables (DD, SAF). Powell (1997) shows that takeover target characteristics are time variant. To test the robustness of our results over time, we estimate models using the whole time period, 1994–2023 (pool 1), and two sub-periods, 1994–2008 (pool 2) and 2009–2023 (pool 3). The regressions are controlled for fixed year effects, and the standard deviations are clustered on a firm-year level. All variables have been standardized to zero mean and unit variance before the regressions to increase comparability.

The results presented in Table 5 are mostly in line with the presupposed hypotheses discussed above and overall, mostly with significant results. Results between the base model and the enhanced model are consistent with each other, however, the explanatory power of the enhanced model is found greater. Our additional hypothesis and augmented variables are found mostly significant and confirmed in our sample. Looking at our pseudo-R^2 values, the goodness of our model is at par with those reported in previous research (Danbolt et al., 2016; Powell & Yawson, 2007; Powell, 2001).

Table 5 – Logistic regressions

This table shows the results of in-sample logistic regressions performed on the base and enhanced models in different time periods. All models include fixed year effects and the variances have been clustered on a firm-year level. All variables have been standardized to zero mean and unit variance before the regressions. Pool 1 refers to the time period between 1994 and 2023, pool 2 to 1994 and 2008, and pool 3 to 2009 and 2023. See Table 4 for explanation on model variables.

	Dependent variable:					
	PTO					
	Base			Enhanced		
	1994-2023	1994-2008	2009-2023	1994-2023	1994-2008	2009-2023
NITA	0.106***	0.114***	0.087**			
LEV	0.107***	0.080***	0.138***			
FCF	0.025	0.02	0.038			
SG	-0.045***	-0.048**	-0.039	-0.029*	-0.031	-0.019
AER	-0.008	0.001	-0.016	-0.066***	-0.072***	-0.043
TQ	-0.165***	-0.207***	-0.107***	-0.218***	-0.255***	-0.155***
LIQ	0.073***	0.091***	0.021	0.035**	0.052**	-0.007
GRD	0.007	-0.005	0.031	0.003	-0.007	0.022
M&A	0.117***	0.123***	0.105***	0.107***	0.117***	0.095***
SIZE	-0.143***	-0.078***	-0.235***	-0.131***	-0.075***	-0.197***
TANG	-0.022	0.019	-0.101***	-0.030*	0.013	-0.118***
AGE	-0.200***	-0.181***	-0.232***	-0.206***	-0.199***	-0.214***
DD				-0.085***	-0.083***	-0.061*
PROF				0.173***	0.148***	0.204***
GROW				0.011	0.050**	-0.058**
SAF				-0.104***	-0.047*	-0.195***
PAY				0.076***	0.102***	0.028
TRD				0.031*	0.034*	0.013
PMOM				0.201***	0.220***	0.159***
SENT				0.014	-0.05	0.06
Constant	-5.619***	-5.532***	-5.766***	-5.645***	-5.567***	-5.786***
Pseudo-R2	1.28 %	1.26 %	1.27 %	1.69 %	1.81 %	1.57 %
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,091,272	660,146	431,126	1,091,272	660,146	431,126
PTOs	4,297	2,826	1,471	4,297	2,826	1,471

Note: *p<0.1; **p<0.05; ***p<0.01

Inefficient management receives somewhat strong evidence in our sample, though mostly contrary to the direction initially anticipated. In the base model, NITA is found to have a significant and positive impact across the subperiods, contrary to the expected direction. Likewise, PROF is identified as an important factor for screening takeover targets, albeit also in a direction contrary to expectations. Thus, both NITA and PROF suggest that higher profitability increases the likelihood of becoming a target. The fact that profitable companies are found more likely targets could be due to more profitable companies being attractive takeover targets in general, implying that profitability measures might not capture the hypothesis of inefficient management that well. AER receives support only in the enhanced model, however, in the expected direction. Interestingly, the impact of GROW is found to change direction between pool 2 and pool 3. In pool 2, growth increases the likelihood of becoming a target, while in pool 3, it decreases.

Firm misvaluation receives strong support as TQ shows strong statistically significant influence throughout the sample and model and has one of the largest absolute coefficients of the independent variables, giving the *misvaluation* hypothesis strong grounds. The sign of the coefficient is also aligned with our hypothesis – companies with lower valuations can be seen as likelier takeover targets.

The growth-resource mismatch hypothesis receives little empirical support in our sample with small and non-significant coefficients throughout model and pool. Although GRD itself receives limited evidence according to results on its subcomponents, companies with better-than-average liquidity positions combined with high leverage and slow recent sales growth seem to be likelier targets. Sales growth (SG), however, loses most of its significance in the enhanced model, perhaps due to the inclusion of the alternative growth variable GROW.

The free cash flow hypothesis receives little evidence as FCF is not found to have an impact on takeover likeliness. However, in the enhanced model the alternative proxy PAY receives statistically significant results, although, in a contrary fashion than expected initially. It seems that the basic FCF proxy fails to capture differences between non-targets and targets, perhaps as it does not measure absolute payout, but rather the theoretical availability of payout. Interestingly, higher payout behaviour seems to increase the likeliness of takeover, contrasting with the hypothesis that takeovers are a way of fixing agency issues relating to the accumulation of free cash flow. It is, however, in line with the notion that appealing acquisition targets for buyout are often financed with high leverage, for which free cash flows are desirable (Jensen, 1986) – higher payout can be shifted towards debt service.

Industry disturbance, firm size, and *age* receive support as, M&A, SIZE, and AGE show strong statistical significance throughout the subperiods with large absolute coefficients. The signs support the hypothesis that smaller companies in industries with large disturbances are likelier PTO targets. Furthermore, AGE is in line with our expectations. Younger firms seem to be likelier takeover targets. Interestingly, TANG is found to have a significant impact on takeover likeliness only in Pool 3 in a direction contrary to expectations. The negative impact of *tangibility* might be the result of the tightening financing conditions in pool 3, whereby companies with higher tangible assets are able to loan capital with lower costs, thus increasing their equity returns, valuation, and financial strength, making them less available for acquisition. Also, the negative coefficient could reflect the characteristics of our PTO sample – most PTOs occur in industries with traditionally light asset structures, such as software.

Stock market activity receives partial evidence with price momentum (PMOM) showing statistical significance in both periods. Trading volume (TRD) is found significant only at 10%

and only in pool 1 and pool 3. Market *sentiment* is not measurable here, as the year dummies capture its impact. When year dummies are excluded from the regressions, it shows strong statistical significance with a positive coefficient.

Firm risk is found statistically significant in all time periods and in the expected direction. DD, representing high distress, is found to have a negative influence on takeover likelihood, and SAF, representing the overall firm risk profile, is found to have a negative influence[1]. Consistent with our hypothesis, the results suggest that firms with higher risk profiles are more likely to become targets for PTOs, provided they are not currently experiencing immediate distress.

Integrating the results, it appears that misvalued, younger, and smaller companies characterized by better-than-average profitability and payout ratios but with higher risk profiles, albeit not in distress, are more likely to be takeover targets. The impact of growth seems to differ between time periods, although its effects are limited overall. Moreover, takeovers tend to occur in industries experiencing disturbances. Additionally, stock price momentum and equity market sentiment are found effective in enhancing the timing ability of the model.

Lastly, to test whether overall firm Quality as per Asness et al. (2018) affects takeover risk we run the enhanced model with the Quality measure without its sub-components (PAY, SAF, GROW, and SAF). As Quality and its sub-components are highly correlated, running them together would make limited sense. In untabulated results we find that firm Quality has a significant positive impact on takeover likeliness, in line with our hypothesis. Hence, interestingly, target companies are found of higher overall Quality, but still show a higher risk profile.

6.2 Predictive accuracy

In the following Sections (6.2-6.3), we begin by developing seven new models, and a benchmark model. As a benchmark, we use a logit model which resembles a model most often used in takeover prediction as explained in Section 5.1[2] Consequently, we examine the robustness of our models and proceed with the two models that demonstrate the best predictive capabilities, along with the benchmark model. Finally, we investigate the ability

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[1] In our framework, high DD implies high distress whereas high SAF implies low distress

[2] Our base model is largely inspired by the "conventional" model used by Danbolt et al. (2016). The model is a logit model that uses the 12 base variables explained in Section 5.1.

of the proposed models to formulate the basis of successful investment strategies, both in a long-only and long-short setting.

6.2.1 Overall predictive performance

We start the evaluation of predictive performance by calculating accuracy, precision, recall, and F1 scores for our models. The models are created from the combinations of four different classification techniques (logit, random forest, gradient boosting, and combined forecast), and two sets of independent variables (base and enhanced). The models predict PTOs in month $t + 1$ with variables known at the end of month t. The models are trained on data trailing month t by 10 years[1]. In the calculations, a firm-month is labelled as one (indicating a PTO-bid) if the month's balanced predicted probability of a PTO exceeds 50%. The performance metrics are defined as:

- **Accuracy** measures the share of correct classifications to all classifications.
- **Precision** measures the share of true positives to the sum of true positives and false positives - how often a predicted positive is a true positive.
- **Recall** measures the share of true positives to the sum of true positives and false negatives - the rate of positives correctly identified from the set of all positives.
- **F1-score** is the harmonic mean of precision and recall. The metric can be interpreted as a holistic measure of how well the model can classify true positives.

For us, the F1-score is the single most important metric when predicting PTOs. In terms of our investment strategy, there's relatively less value in identifying true negatives than there is in identifying true positives, as true positives bring most of the profits. Thus, we aim to identify as many positives as accurately as possible, both being aspects captured by the F1 score. Most previous literature has optimized takeover models in maximum likelihood estimation (MLE) fashion (i.a. Powell and Yawson (2007) & Danbolt et al. (2016)). We, however, deviate from this as MLE is indifferent to the type of errors (false positives vs. false negatives) in standard form.

Table 6 summarizes the results on predictive performance over models and techniques. Comparing the results of models trained on base and enhanced variables, we observe that nearly all F1 scores are improved in the enhanced specification. Thus, as supported by the increased pseudo-R^2 values in the logit regressions shown in Table 5, we can conclude that the use of enhanced variables increases predictive accuracy.

[1] See Figure A2 in the Appendix for more details

Table 6 – Predictive performance per model

This table shows the average monthly predictive performance per model and classification technique. Firm-months with predicted probabilities of takeover exceeding 50% are categorized as PTO firm-months. Accuracy measures the share of correct classifications to all classifications. Precision measures the share of true positives to the sum of true positives and false positives. Recall measures the share of true positives to the sum of true positives and false negatives. F1-score is the harmonic mean of precision and recall.

Model	Base model				Enhanced model			
Classification technique	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
Logit	63.93 %	0.48 %	47.60 %	0.95 %	64.06 %	0.50 %	49.59 %	0.98 %
Random forest	90.16 %	0.70 %	18.07 %	1.34 %	89.60 %	0.65 %	18.55 %	1.25 %
Gradient boosting	97.63 %	0.65 %	4.01 %	1.09 %	97.98 %	0.76 %	3.51 %	1.20 %
Forecast combination	96.40 %	0.76 %	6.91 %	1.34 %	96.25 %	0.90 %	8.60 %	1.58 %

Comparing the performance of classification techniques within the same set of independent variables, we find even larger absolute differences in F1 scores. Logit has the weakest results regarding this metric, while forecast combination, interestingly, delivers the best performance. Overall, it seems that the classification technique matters more than the set of variables when maximizing predictive performance.

If we were to invest in all companies classified to receive a PTO bid based on the 50% rule, the number of companies included in the portfolios of each technique would grow large and volatile (a monthly average of ~50-950 with a volatility of ~25-250), making the classification method difficult to implement as an investment strategy. Thus, to build portfolios that are more practical in size, we formulate[1] equally weighted portfolios with 25, 50, 75 and 100 companies with the highest modelled probability of takeover. We refer generally to these portfolios as top X portfolios.

When comparing the results of equally weighted top X portfolios, we focus on concentration ratios presented in Table 7. Concentration ratios measure the percentage of correctly predicted targets over the total number of stocks in the portfolio. Surprisingly, most models trained on base variables have better or equal concentration ratios when compared to models trained on enhanced variables. It seems that the enhanced models start to perform better only when more stocks are included in the portfolios. Of the base and enhanced specifications, base random forest and enhanced forecast combination have the highest concentration ratios. Given the strong results of the two, we analyze them further and calculate portfolio returns for them. The results are then benchmarked to the returns of the base logit model.

[1] Most papers (for instance, Danbolt et al. (2016) and Brar et al. (2009)) invest in the top X -percentage of companies each period. For simplicity, we decide to invest in a constant number of firms.

Table 7 – Top X portfolio concentrations

This table describes the average monthly concentrations per model and technique. Each portfolio includes top 25, 50, 75 or 100 companies calculated to have the highest probability of receiving a PTO bid. Concentration ratio is defined as: correctly predicted targets over total number of stocks in the monthly portfolio.

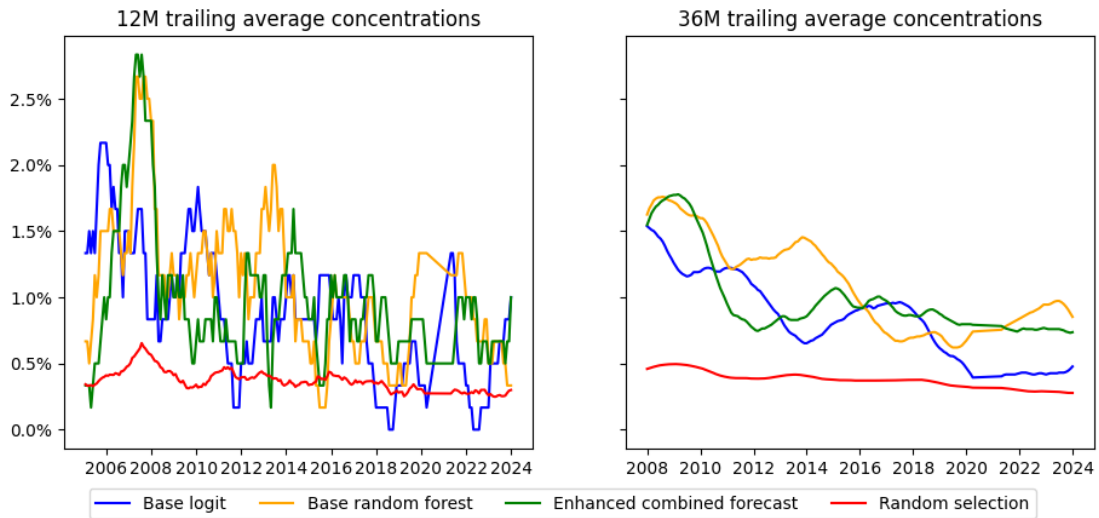
Model	Base model				Enhanced model			
Concentration	Top 25	Top 50	Top 75	Top 100	Top 25	Top 50	Top 75	Top 100
Logit	0.79 %	0.89 %	0.80 %	0.74 %	0.79 %	0.83 %	0.72 %	0.77 %
Random forest	1.26 %	1.05 %	0.86 %	0.80 %	0.94 %	0.90 %	0.85 %	0.75 %
Gradient boosting	0.75 %	0.73 %	0.68 %	0.64 %	0.84 %	0.71 %	0.70 %	0.69 %
Forecast combination	1.21 %	0.91 %	0.83 %	0.79 %	1.10 %	0.94 %	0.85 %	0.84 %

Overall, while the concentration ratios may appear modest, they are encouraging given the complexity of the question addressed. For example, the proportion of PTO firm-months to all firm-months in the investment period from 2004 to 2023 is only 0.36%. This indicates that by random selection one should expect to have a monthly concentration ratio of around 0.36%. Looking at our results, we can see that we are double to triple to the magnitude of random selection. For instance, the enhanced forecast combination's top 25 portfolio achieves a concentration ratio ~3 times higher.

Furthermore, looking at Figure 2 presenting the average trailing 12-month and 36-month concentration ratios for the top 50 portfolios, we find that our performance above random selection is not due to a small number of extremely good periods, but rather due to stable performance. Looking at the right panel with the 36-month results, we find that during no three-year period are we under the performance of what one would expect to achieve with random selection in any of the three models in the top 50 firms framework.

Figure 2 – Trailing average concentration ratios for top 50 portfolios

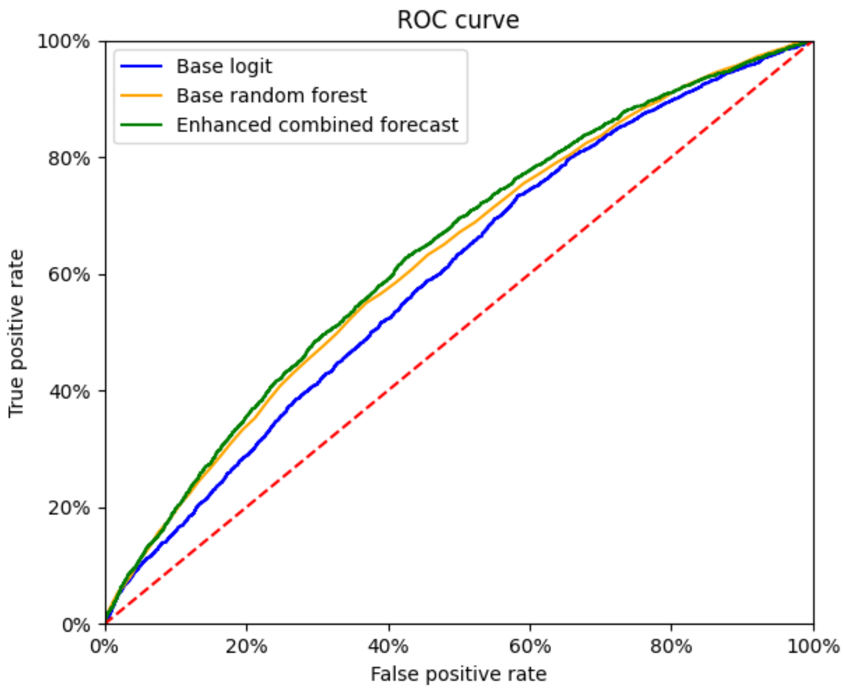
This figure describes the trailing average monthly concentration ratios for the selected models. Each portfolio includes 50 companies calculated to have the highest probability of takeover. Concentration ratio is defined as: correctly predicted targets over total number of stocks in the monthly portfolio.



It's surprising that models trained on the base variables have similar or higher concentration ratios than the models trained on the enhanced variables, given that the F1-scores between the specifications differ significantly in the opposite direction. For example, base random forest's concentration ratios are higher or on par when compared to enhanced forecast combination, even though enhanced forecast combination's F1-score is 1.58% and base random forest's only 1.34%. However, looking at the models' ROC-curves presented in Figure 3, it seems that significant differences in predictive performance are born only in the middle of the probability distributions, not in the tails[1]. Given that our top X portfolio approach is focused on one tail of the distribution, it's evident why the better F1-scores cannot be seen in the concentration ratios.

Figure 3 – ROC curve

This figure plots the receiver operating characteristic curves (ROC) measuring the relationship between true positives and false positives for the selected models. The area under the curve (AUC) quantifies the overall ability of the model to discriminate between positive and negative classes, with a higher AUC indicating better performance.



Our models demonstrate a clear improvement over the results documented in prior studies. To contextualize our performance against existing literature, we examine the concentration ratios relative to the base distribution. Note that our best models achieve a concentration

[1] This can be seen in Figure 3 as the ROC curve of the base logit is close to that of the base random forest and enhanced combined forecast only in the tails. The higher the area beneath the ROC curve, the better the model performs. Hence, the base random forest and enhanced combined forecast perform better only in the middle of the distribution.

ratio over three times the ratio of the underlying distribution. In comparison, Ouzounis et al. (2009) report a concentration ratio of 20.3% in their best model with a sample containing 9.4% of PTOs. Hence, their concentration ratio is only 2.2 times that of the underlying distribution. Similarly, Danbolt et al. (2016) report a concentration ratio of 8.5% with an underlying distribution of 5.1% (1.7 times). Furthermore, both papers utilize yearly investment periods instead of monthly ones, making it around 12 times easier to get a correct forecast. Hence, our model performs clearly better. This is evident also when compared to Brar et al. (2009), who achieve a concentration ratio of 0.7% against a base distribution of 0.5% using a monthly specification.

6.2.2 Tests between monthly and yearly portfolio formation

In addition to comparing models across variables and techniques, we test them in both monthly and yearly investment frameworks. In the alternative yearly specification, companies are chosen for the portfolios at the end of the year and held for the following 12 months. Unfortunately, the results between the frameworks are not exactly comparable due to the different time intervals. For example, precision and concentration tend to increase linearly with time as the predictions have a longer window to be correct (1 month vs 12 months). On the other hand, recall might stay constant or vary, depending on whether the number of PTOs overall increases linearly with the number of PTO hits. As rules of thumb, we adjust both annual precision and concentration by dividing the numbers by 12 and assume recall to stay constant over time, leaving it unadjusted in both models. The F1-score can then be derived from the adjusted figures.

In untabulated results, models including the base variables have similar predictive power both in the monthly and annual framework. This is an expected result, as many of the variables used in the base models have strong autocorrelation within one year and the characteristics of PTO-targets in general could be argued to be persistent across 12 months. However, the enhanced models perform clearly better in the monthly framework. This is also rather expected, as the enhanced models utilize monthly timing variables, such as price momentum. In general, the inclusion of timing variables would be difficult to implement in an annual setup. Finally, the highest adjusted F1-scores and concentration ratios are achieved in the monthly framework, indicating that the monthly specification is best suited for catching PTOs.

6.3 Portfolio returns

In this section, we calculate the returns of portfolios that invest in firms with the highest probabilities of takeover. We begin by analysing long-only returns in comparison to the S&P500, Fama-French three, and momentum frameworks. We then further examine the sources of these returns by decomposing them into smaller subcomponents. Finally, we implement long-short strategies, aiming to create a portfolio that is market and possibly factor-neutral, whilst still generating returns from PTOs.

Utilizing past 10-year rolling windows, our strategy spans from 2004 to 2023. The portfolios are rebalanced monthly. At the end of each month t we invest in the 25, 50, 75, and 100[1] firms with the highest modelled probabilities of takeover during the next month $t + 1$[2]. The portfolios are equally weighted, and probabilities are recalculated monthly. No discretion is used in portfolio construction – the companies are selected for the portfolios solely on the estimated probabilities.

6.3.1 Return time-series and factor analysis

Figure 4 plots the cumulative returns of equally weighted portfolios that invest in the 50 firms with the highest probabilities of takeover, and the S&P500 index. Returns are shown with a logged y-axis. In addition to the portfolio returns (labeled as "inc. all"), we calculate the returns excluding firm-months with PTO hits (labeled as "exc. PTOs") to get a clue on the magnitude of the returns that come solely from the inclusion of PTO firm-months and their announcement returns. Interestingly, the base logit model has the highest returns across models. Also, all three models outperform the market and clearly benefit from hitting PTOs.

Examining the risk-adjusted returns in Table 8, we observe that the base logit model and the enhanced combined forecast model generate abnormal returns in the Fama-French three and momentum framework at 1% significance, and the base random forest at 10% significance. The base logit's abnormal returns retain their significance even without the PTO hits, while the abnormal returns of the enhanced combined forecast and base random forest models lose significance when PTO hits are excluded from the returns. All in all, exposures to the risk factors are similar across models as shown in Table 8. When comparing our abnormal returns to those reported by previous studies (see Table 1), our long-only returns

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[1] In essence we formulate portfolios of different sizes to understand the impact of the portfolio's size

[2] See Figure A2 in the Appendix for more details.

are comparable to the highest previously reported. However, previous studies adjusted for fewer risk factors, which could affect the results.

The alphas generated by the three models remain relatively stable through time, as seen in Figure 4, panel B. Notably, the base logit model generates a monthly alpha of 0.4% or more throughout the 60-month rolling samples. The enhanced combined, however, seems to lose its alpha-generating abilities in the last years of the sample. This is cumbersome as per Figure 2 the concentration ratios do not decrease coming into the corresponding period.

Figure 4 – Return time-series for top 50 portfolios

This figure describes the cumulative returns of the strategies' top 50 portfolios and the S&P500 index on a logged y-scale. The solid lines show the aggregate strategy returns, while the dashed lines show the returns excluding firm-months with PTOs. Alphas are calculated in the Fama-French 3 and momentum framework.

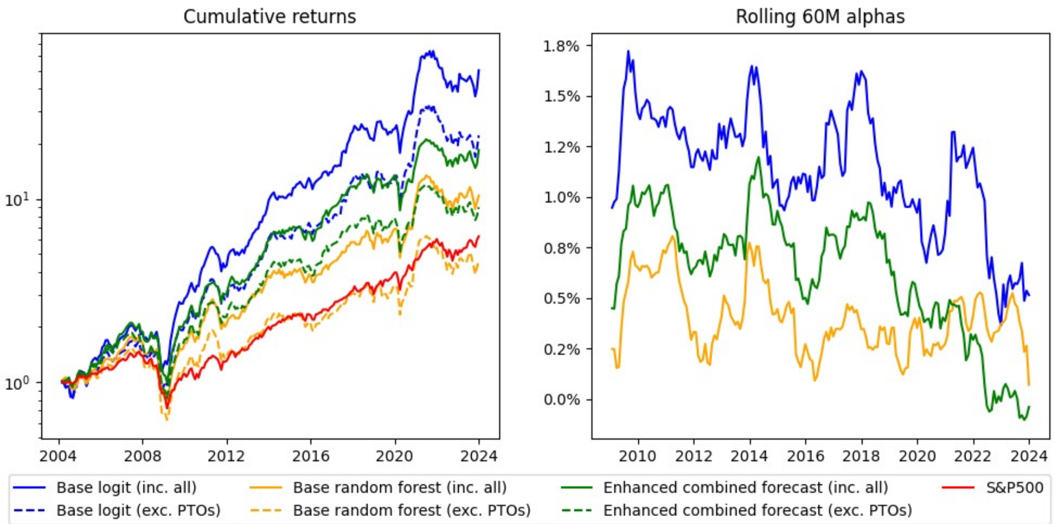


Table 8 – Risk-adjusted model returns for top 50 portfolios

This table presents the model returns adjusted for the Fama-French three and Momentum factors. "Inc. all" refers to model returns including both firm-months with and without PTO hits whereas "Exc. PTOs" refers to model returns excluding firm-months with PTO hits.

	Dependent variable:					
	Base logit		Base random forest		Enhanced combined forecast	
	Inc. all	Exc. PTOs	Inc. all	Exc. PTOs	Inc. all	Exc. PTOs
MKT	0.956***	0.966***	0.982***	0.991***	0.917***	0.915***
SMB	0.977***	0.924***	0.892***	0.870***	0.861***	0.834***
HML	-0.089	-0.084	0.082	0.067	0.121**	0.111**
MOM	-0.206***	-0.160***	-0.105**	-0.102***	-0.106**	-0.113***
Constant	1.0%***	0.7%***	0.3%*	-0.1%	0.6%***	0.3%*
Adjusted R^2	71 %	72 %	85 %	86 %	82 %	83 %

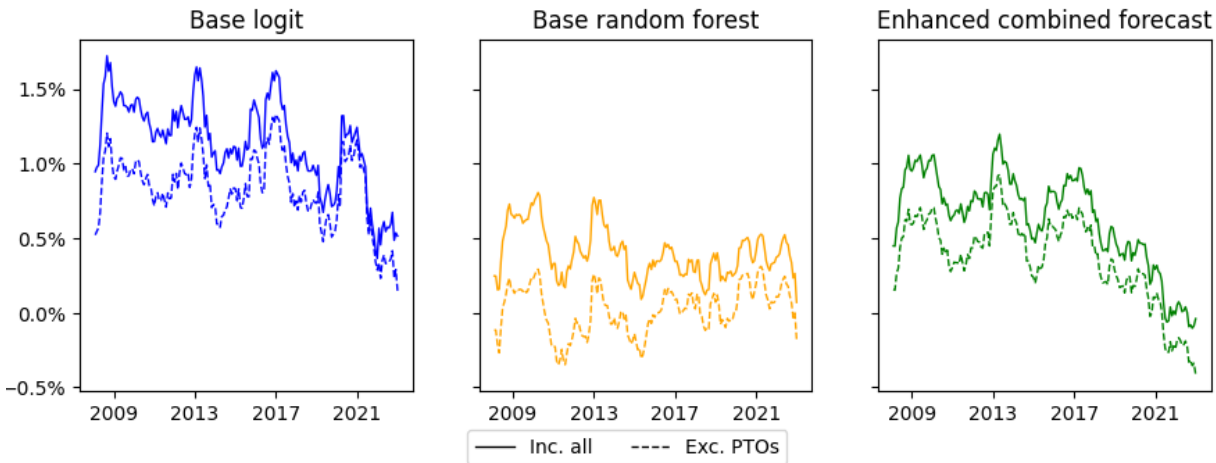
Note: *p<10%; **p<5%; ***p<1%

To further analyze the alpha decay, we plot the rolling alphas per strategy in Figure 5 for both the portfolio returns (inc. all) and returns excluding PTO hits (exc. PTOs). Hence, the gap between the two lines visualizes the alpha that comes solely from the inclusion of PTO firm-months. Looking at the time-series, we can see that the positive impact of hitting PTOs alpha-wise remains roughly the same throughout the whole investment period. However, the alpha sourced from other factors than PTOs seems to degrade, which then diminishes the overall rolling 5-year alphas, especially in the enhanced combined forecast strategy.

All in all, the strategies' return profiles and alpha generating capabilities seem to differ significantly despite their similar theoretical backgrounds. Also, high/low concentration ratios do not directly result in high/low alphas, such as in the case of the base logit model. To better understand the differences between the strategies, we continue our analysis by splitting them into returns gained from PTO hits and returns gained from other return sources.

Figure 5 – Rolling abnormal returns for top 50 portfolios

This figure plots the rolling 60-month alphas for the three top 50 portfolios in the Fama-French 3 and momentum framework. The solid lines plot alphas calculated from the aggregate portfolio returns (Inc. all), while the dashed lines plot alphas calculated from portfolio returns that exclude firm-months with PTOs (Exc. PTOs).



6.3.2 Return sub-component analysis

To further analyse the returns per strategy, we split them into two hypothetical portfolios: a portfolio containing only firm-months with PTOs, and a portfolio containing only firm-months without PTOs.[1] The return characteristics and hypothetical weights of both portfolios as part

[1] For clarity, this approach differs from the approach in Section 6.3.1 by giving each sub-portfolio its corresponding theoretical weight. Hence, the portfolios are related: Exc. PTOs is the unweighted return of the non-PTO portfolio in this section. Inc. all is equal to the weighted sum of the PTO and non-PTO portfolio. In other words, Section 6.3.1 focuses on understanding the contribution of PTOs in relation to a portfolio without PTOs in a time series. In contrary, this section focuses on understanding differences in PTO returns and non-PTO returns between the strategies.

of the aggregate strategies are shown in Table 9. When looking at the results, we notice that the strategies have significant differences in the returns gained from the non-PTO portfolio. For instance, the base random forest only receives 0.8% monthly from the non-PTO portfolio compared to 1.5% of the base logit.

As the aggregate portfolios consist mostly of non-PTO companies, the differences in non-PTO returns likely explain a large part of the deviant performance. For example, a 10% difference in PTO-portfolio returns with a weight of 1% contributes only by 0.1% at the aggregate level, whereas a 0.7% difference in non-PTO portfolio returns with a weight of 99% contributes by 0.69% at the aggregate level.

It's cumbersome that the non-PTO returns differ that significantly, even though the underlying models that generate the strategies share many common features. To get deeper into the root causes of the differences, we divide the returns further into a market factor and two hypothetical factors: a non-PTO factor and a PTO factor. The non-PTO factor is simply assumed to contain the market-adjusted returns of non-PTO companies, while the PTO factor is assumed to contain the market-adjusted returns of PTO companies. The division helps us to allocate the returns above market to different sources and evaluate their impact per strategy. Let's assume that we can define any portfolio P as:

$$P = r_f + \beta_1(r_m - r_f) + \beta_2 NONPTO + \beta_3 PTO.$$

Table 9 – Return characteristics of hypothetical PTO and non-PTO portfolios

This table presents the average monthly return profiles of the hypothetical PTO and non-PTO portfolios. The hypothetical portfolios together form the aggregate returns per strategy. The PTO portfolio includes only firm-months with PTOs, while the non-PTO portfolio includes only firm-months without PTOs. The Sharpe ratios are calculated as gross values.

		PTO portfolio				Non-PTO portfolio			
Model	Metric	Top 25	Top 50	Top 75	Top 100	Top 25	Top 50	Top 75	Top 100
Base logit	Return	39.8 %	41.5 %	40.9 %	38.1 %	1.5 %	1.5 %	1.6 %	1.5 %
	Volatility	27.6 %	47.8 %	45.0 %	42.6 %	7.2 %	6.8 %	6.7 %	6.8 %
	G. Sharpe	4.99	3.01	3.15	3.09	0.71	0.78	0.80	0.75
	Weight	0.8 %	0.9 %	0.8 %	0.7 %	99.2 %	99.1 %	99.2 %	99.3 %
Base random forest	Return	37.0 %	34.4 %	33.7 %	34.2 %	0.8 %	0.8 %	0.8 %	0.8 %
	Volatility	29.1 %	25.3 %	22.3 %	23.8 %	6.3 %	6.2 %	6.2 %	6.2 %
	G. Sharpe	4.40	4.71	5.24	4.98	0.42	0.46	0.44	0.44
	Weight	1.3 %	1.0 %	0.9 %	0.8 %	98.7 %	99.0 %	99.1 %	99.2 %
Enhanced combined forecast	Return	30.5 %	33.3 %	32.1 %	32.4 %	1.1 %	1.1 %	1.1 %	1.1 %
	Volatility	18.9 %	29.8 %	28.5 %	27.0 %	5.9 %	6.0 %	5.9 %	6.0 %
	G. Sharpe	5.60	3.87	3.90	4.15	0.68	0.64	0.64	0.60
	Weight	1.1 %	1.0 %	0.8 %	0.8 %	98.9 %	99.0 %	99.2 %	99.2 %

By definition, the non-PTO portfolio must contain only non-PTO firm-months and have exposures to the market factor and the non-PTO factor. Similarly, the PTO portfolio must contain only PTO firm-months and have exposures to the market factor and the PTO factor. The portfolios can be then defined as:

$$P_{NONPTO} = r_f + \beta_1(r_m - r_f) + \beta_2 NONPTO$$
$$P_{PTO} = r_f + \beta_1(r_m - r_f) + \beta_3 PTO.$$

To simplify further, non-PTO companies could be assumed to have average market betas of one if they are selected uniformly from the stock universe and systematic risk is not a key driver in the models. This assumption is supported by our factor regressions in Table 8, where all three top 50 portfolios, consisting mostly of non-PTO companies, have market betas close to one. Similarly, as the stock prices of companies under a PTO-bid could be assumed to be driven by the offer price and probability of deal completion instead of systematic factors, we could expect their market betas to be close to zero. Thus, by assuming the portfolios' market betas to be one and zero, we can estimate them as:

$$P_{NONPTO} = r_m + \beta_2 NONPTO$$
$$P_{PTO} = r_f + \beta_3 PTO.$$

Given the equal returns gained from the market factor and risk-free rate across strategies and portfolios, the two equations allow us to estimate that all return variation between the models must come from varying exposures to the non-PTO and PTO factors. As most of the aggregate return variation can be explained by the non-PTO returns due to their large weights, and variation in non-PTO returns is caused by the different non-PTO factor exposures, we can conclude that the strategies' divergent returns aren't necessarily explained by PTO hits. Instead, they are explained by other factor exposures. In Table A1[1] we can see that non-PTO factor returns at the hypothetical non-PTO portfolio level are 0.6%-0.7% for base logit, -0.1%-0.0% for base random forest, and 0.2%-0.3% for enhanced forecast combination.

6.3.3 Reasons behind diverging non-PTO return performance

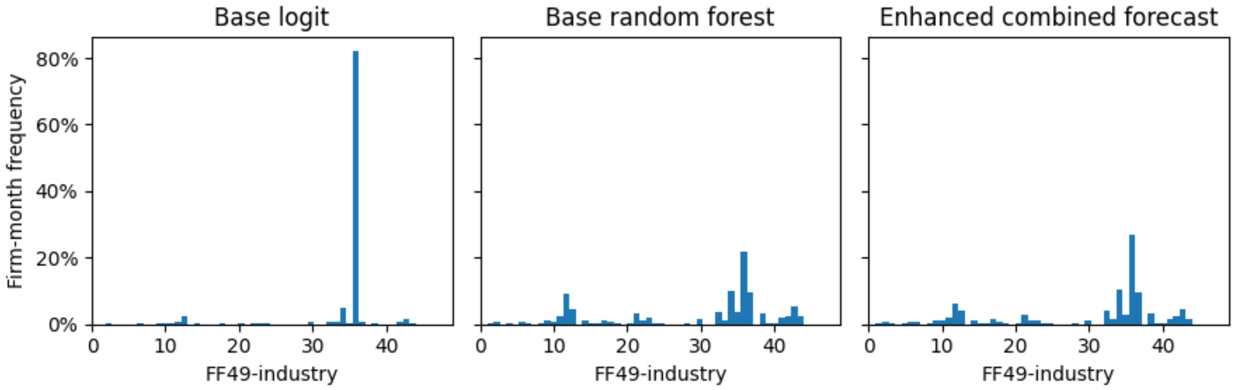
To better understand the deviations in non-PTO returns, we look at the characteristics of the different portfolios. First, we analyze the industry distributions of each strategy by categorizing the portfolios on Fama-French 49 industries as shown in Figure 6. Looking at

[1] See Table A1 in the Appendix for more information

the distributions, we can see that the base logit model invests almost solely in software companies, whereas the other two strategies have more balanced and similar firm-month industry distributions. Thus, base logit's deviant non-PTO factor returns most likely come from its unique industry focus.[1]

Figure 6 – Portfolio firm frequencies between industries

This figure presents the distribution of portfolio firm-months between Fama-French 49 industries averaged across top-X portfolios. The highest frequency is 36 – software.



But then again, there is no clear difference in industry exposure between the base random forest and enhanced combined forecast models, even though their non-PTO factor returns differ significantly. To better understand this deviation, we examine a core distinction between the two models: the different sets of explanatory variables. The enhanced combined forecast model incorporates more sophisticated Quality, distress, and momentum metrics, which are shown to have an impact on returns (Asness et al., 2018; Campbell et al., 2008; Moskowitz et al., 2012)

Looking at the averages of the independent variables across strategies shown in Table 11, we can see that the enhanced combined forecast model has more favorable factor exposures than the base random forest model. Enhanced combined forecast scores significantly better on Profitability, Growth, Payout, and Price momentum, and is on par in other metrics, indicating that enhanced combined forecast's solid non-PTO factor returns could come from more positive loadings on Quality and momentum factors. Consequently, base random forest's unimpressive non-PTO factor returns could be the result of more unfavorable or neutral exposures to the same factors. Surprisingly, base logit has significant favorable

[1] The software industry witnesses most PTOs in our sample. Thus, it could be that the logit model seeks to maximize fit by weighing industry-specific variables (such as M&A) in the regressions, leading to extremely concentrated industry positions. We believe that random forest and enhanced combined forecast don't have the same bias due to the utilization of weak learners when making predictions.

exposures to some components on the Quality factor even though Quality's subcomponents are not included in the base model, possibly being the result of the significant industry focus.

Table 11 – Selected portfolio characteristics

This table presents the averages of selected explanatory variables per portfolio The variables are calculated by averaging the characteristics of all firms selected for the portfolios during the 20-year investment period. See Table 4 for explanation on model variables.

Model	Portfolio	PROF	GROW	SAF	PAY	DD	TRD	PMOM
Base logit	Top 25	0.28	-0.07	0.07	-0.05	2.03 %	-0.03	-0.02
	Top 50	0.27	-0.05	0.04	-0.06	2.11 %	-0.02	-0.01
	Top 75	0.25	-0.05	0.03	-0.05	2.40 %	0.01	-0.01
	Top 100	0.22	-0.06	0.02	-0.05	2.58 %	0.02	-0.02
Base random forest	Top 25	0.05	-0.23	0.06	-0.11	0.57 %	-0.06	-0.01
	Top 50	0.04	-0.24	0.07	-0.08	0.67 %	-0.05	0.00
	Top 75	0.04	-0.24	0.07	-0.07	0.70 %	-0.05	-0.01
	Top 100	0.04	-0.24	0.07	-0.06	0.79 %	-0.04	-0.01
Enhanced combined forecast	Top 25	0.26	-0.17	0.05	0.10	0.48 %	-0.03	0.17
	Top 50	0.25	-0.18	0.05	0.11	0.53 %	-0.04	0.15
	Top 75	0.24	-0.18	0.05	0.12	0.57 %	-0.04	0.15
	Top 100	0.23	-0.17	0.05	0.12	0.60 %	-0.04	0.14

6.3.4 Long-short strategies

All in all, the results suggest that the models are fairly similar in their ability to generate returns from PTO hits, but different in their ability to capture returns outside of PTOs. Even though some of the non-PTO factor returns clearly boost the strategies' performance (especially in the base logit model), we are essentially after the PTO returns due to their excellent Sharpe ratios and independence from traditional asset pricing factors. Hence, we look for ways to further isolate PTO returns from other returns captured by the portfolios.

To catch the PTO returns, we identify two practical plays: 1) investing in the top X portfolios and shorting the whole market, and 2) narrowing the strategy down to top X portfolios investing solely in one industry and then shorting the corresponding industry. As the software industry peaks in each of the three models analyzed and is the most frequent industry in our underlying PTO sample, we use it as a benchmark. Table 12 includes monthly return statistics for both long-short strategies.

Of the two different long-short approaches, the long-short software industry strategy works better with generally higher Sharpe ratios, greater factor independence, and more significant alphas. The long-short market strategy seems to just suppress market betas to zero but leave the returns otherwise intact. The long-short software industry strategy, on the other hand, captures more of the non-PTO factor returns in addition to the market returns, leaving the strategy significantly less exposed and almost neutral to any traditional asset pricing factors.

Interestingly, all three models generate statistically significant alphas in the long-short software industry framework, implying that with an adequate short leg, many different PTO-prediction strategies can yield significant abnormal returns. However, in the long-short market framework, only base logit and enhanced combined forecast models yield significant alphas, resembling the returns of the long-only strategies. The result is interesting as it essentially implies that by creating better short legs one could potentially enhance takeover portfolio return profiles without improving the predictive capability of models themselves.

Table 12 – Returns of long-short portfolios

This table presents the return characteristics of long-short portfolios formed with different portfolio sizes. The long-short market strategy is long into the top 25-100 firms with the highest takeover likeliness and short the Fama-French overall market. The long-short software industry is long into the top 25-100 firms with the highest takeover likeliness in the software industry and short the equally weighted software industry (software = Fama-French industry 36). The Sharpe ratios are calculated as gross values. Risk factors are calculated for the top 50 portfolio.

		Long-short market				Long-short software industry			
Model	Metric	Top 25	Top 50	Top 75	Top 100	Top 25	Top 50	Top 75	Top 100
Base logit	Return	0.89 %	1.02 %	0.99 %	0.87 %	0.80 %	0.79 %	0.78 %	0.56 %
	Volatility	5.22 %	4.58 %	4.31 %	4.20 %	3.96 %	2.61 %	2.30 %	1.93 %
	G. Sharpe	0.59	0.77	0.80	0.72	0.70	1.04	1.17	1.00
Base random forest	Return	0.35 %	0.31 %	0.18 %	0.17 %	0.16 %	0.29 %	0.23 %	0.17 %
	Volatility	3.67 %	3.38 %	3.18 %	3.13 %	3.23 %	2.28 %	1.99 %	1.69 %
	G. Sharpe	0.33	0.32	0.20	0.19	0.17	0.45	0.40	0.35
Enhanced combined forecast	Return	0.60 %	0.54 %	0.47 %	0.43 %	0.41 %	0.50 %	0.41 %	0.37 %
	Volatility	3.63 %	3.39 %	3.20 %	3.08 %	3.35 %	2.39 %	1.95 %	1.85 %
	G. Sharpe	0.57	0.55	0.51	0.48	0.43	0.73	0.72	0.69

Long-short strategies

	Dependent variable:					
	Long-short market			Long-short software industry		
	Base logit	Base random forest	Enh. combined forecast	Base logit	Base random forest	Enh. combined forecast
MKT	-0.044	-0.039	-0.100**	-0.118***	-0.091**	-0.107***
SMB	0.977***	0.904***	0.870***	-0.01	0.021	-0.08
HML	-0.089	0.099*	0.076	0.137**	0.139***	0.245***
MOM	-0.206***	-0.104**	-0.082*	-0.083*	-0.007	0.029
Constant	1.0%***	0.2%	0.5%***	0.9%***	0.4%**	0.6%***
Adjusted R^2	32 %	47 %	38 %	6 %	4 %	12 %
Note:						*p<10%; **p<5%; ***p<1%

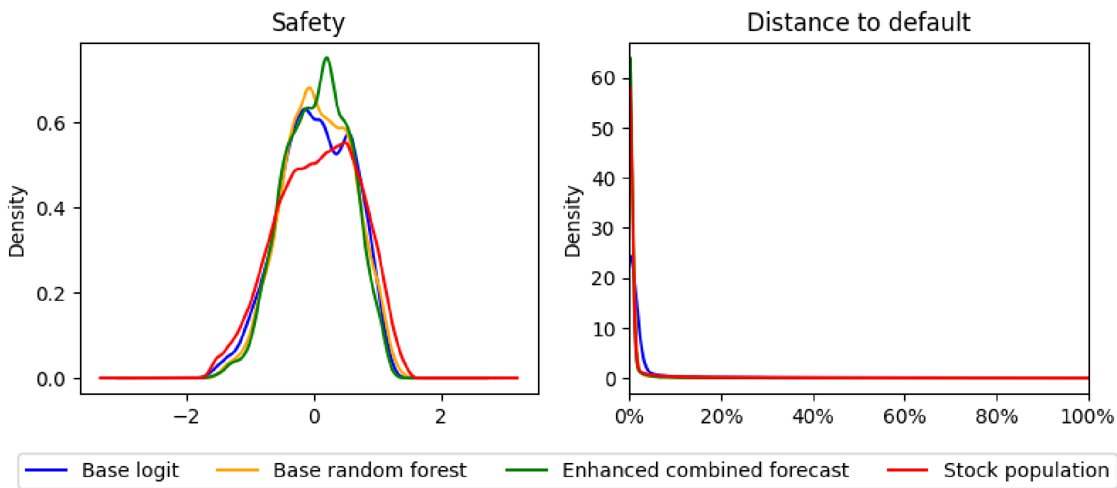
6.3.5 The effect of financial distress on portfolio performance

All three top 50 long-only portfolios generate significant alphas at the 10% threshold and two at the 1% threshold. The result is impressive considering that none of the portfolios contain any firm-level distress filters, which were deemed essential by Danbolt et al. (2016) to generate alpha with PTO prediction in the first place. The level of alpha generation indicates that our models do not suffer from misclassifying distressed entities as PTO targets. Also, applying distress screens based on Distance to default does not improve portfolio returns in our sample. Instead, the screened portfolios have similar or weaker return profiles when compared to non-screened portfolios.

To further test the hypothesis of distress, we present the kernel density estimate plots of Safety and Distance to Default for the top 50 portfolios and the underlying stock universe in Figure 7. For Safety, the left tails of the three portfolios are narrower than those of the stock population, indicating less tail risk for our portfolios when considering firm-months on a going concern basis. However, the portfolios show a slight left tilt at the center of the distribution, suggesting higher overall riskiness from a Safety perspective, as anticipated by our hypothesis. Regarding Distance to Default, the right tail of the base logit slightly exceeds that of the underlying distribution, indicating some signs of distress. Despite this, even the base logit's tail converges to zero before the 10% mark, suggesting that the level of distress is not severe in any of the portfolios. Overall, the riskiness of the portfolios closely follows that of the underlying stock population, with only a minor increase in risk when measured by Safety.

Figure 7 – Safety and Distance to default KDEs in top 50 portfolios

This figure plots the kernel density estimates for Safety and Distance to default for the three top 50 portfolios and the underlying stock population in the investment period from 2004 to 2023. In the Distance to default figure, base random forest's and enhanced combined forecast's plots cannot be seen as they are covered by the plot of "Stock population".



6.3.6 Limitations to PTO-prediction

Given the impressive returns gained from PTO prediction, it is important to note limitations related to the strategy. First, as implied by the strong factor exposures to SMB, the models invest primarily in small-cap stocks with the average market capitalization being ~$630 million across models. However, this should not be surprising given that most PTO bids in our sample are announced on small-cap companies. Yet, the focus makes the strategy viable only for smaller capital allocations.

Second, the predicted probabilities of takeover are rather volatile throughout the models, leading to varying probability ranks between companies and numerous trades each month. For example, the average number of companies held in enhanced combined forecast's top 100 portfolio in subsequent months is only 39 implying that, on average, 61 companies are turned over each month. Considering the focus on small-cap stocks and the need for frequent rebalancing, the strategy begins to seem impractical. Luckily, the number of trades can be decreased by including fewer companies in the portfolios and rebalancing less frequently.

Finally, it's important to remember that the choice of an industry ex-ante in the long-short industry framework is not straightforward. Even though the maturity and M&A frequency of an industry can be predicted quite reliably, it's impossible to know exactly what the future holds. Nonetheless, the industry specification should be rather easy to scale to span multiple industries, making it more effective and diversified in practice.

7. Conclusion

A large body of research has investigated whether abnormal returns can be earned by investing in firms with high predicted probabilities of becoming takeover targets. Most studies, however, conclude that such a strategy is unlikely to yield constant abnormal returns for its investors. The latest research on the topic suggests that prediction errors, poor timing, and misclassifying bankrupt firms as potential targets have principal effects in diluting returns. In this study, we contribute to the existing literature by examining and proposing ways to reduce or mitigate these challenges, with the aim of generating abnormal returns. Whilst doing so, we also present new unknown information on the characteristics of PTO targets.

In terms of predictive accuracy, we find that more advanced modelling techniques, such as gradient boosting, random forest, and forecast combination, significantly increase predictive performance. The inclusion of more advanced variables also contributes to model performance, but at more limited scale. We find that the inclusion of an additional hypothesis, *firm risk*, enhances the model's ability to identify differences in targets and non-targets as well as distinguish between actual targets and distressed entities. Furthermore, by adopting a monthly framework and incorporating variables such as price momentum and market sentiment, we enhance the model's timing capabilities.

Promisingly, all models beat random selection by a magnitude of nearly double that of random selection, with the best model being more than 3.3 times better. Moreover, our suggested enhancements improve model performance by up to 65% compared to the benchmark logit model, as measured by F1-scores. Furthermore, we find that our overall performance above random selection is not due to a small number of extremely good periods, but rather due to stable performance, giving strong grounds for the formation of our investment strategy. All in all, our models demonstrate a clear improvement over the results documented in prior studies.

In terms of portfolio performance, we find that all our models overperform the market and generate significant abnormal returns in the Fama-French three and momentum framework. When comparing our long-only abnormal returns to those reported by previous studies, our long-only returns are comparable to the highest previously reported. We find that differences between model returns are often caused by varying factor exposures[1] instead of the ability

[1] By factor exposures we refer to other asset pricing factors than the market and PTOs occurrence

to find PTOs. To mitigate the return effects of other factors than PTOs, we create long-short strategies. Our most successful long-short strategy generates significant monthly abnormal returns of 0.9% and achieves near factor-neutrality in the Fama-French three and momentum framework.

Our research contributes to existing literature through multiple avenues. First, our additional hypotheses not only improve model performance but also provide deeper insights into the characteristics of potential takeover targets. To our knowledge, our approach is the first of its kind to use two risk measures (Distance to default and Safety) to differentiate between various levels of firm risk. Previous literature suggests that PTO targets are companies with high leverage and low liquidity. Our framework reveals that PTO targets are, on average, firms with higher risk profiles, provided they are not currently experiencing immediate distress. Moreover, our paper is to our knowledge the first to incorporate the Quality measure by Asness et al. (2018) into takeover prediction. Doing so, we find that although riskier, PTO targets are of higher overall Quality. These distinctions raise questions on how well not only the drivers behind PTO activity, but also the ideal features of PTO targets are understood.

Furthermore, to our knowledge, our paper is the first academic work focusing on takeover prediction and the related investment strategies in the US in over a decade. Our sample covers most US companies over the span of 30 years, as opposed to the significantly smaller sample sizes utilized previously in the literature. In addition, we are among the very first to adopt a monthly forecasting framework and use the latest classification algorithms. We are also the first to form a long-short strategy that seeks to isolate the returns gained from PTOs.

Lastly, our study has future implications for takeover prediction. Our findings reveal that the selected model framework has more impact on predictive performance than variable selection, and thus, future studies should focus on the classification problem from a technical point of view. Furthermore, as we show that even with a very basic short leg, other non-PTO exposures can be essentially traded away, further research would benefit from the development of better long-short strategies, especially focusing on the short leg.

In conclusion, while predicting takeovers remains challenging, our research demonstrates that it is possible to achieve abnormal returns by utilizing more advanced modelling techniques, new variables, and a long-short strategy. Moreover, this study not only fills a critical gap in the literature but also offers practical applications for investment strategies based on takeover prediction, as well as new insights into the characteristics of PTO targets.

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Appendix

Additional variable definitions

Following Asness et al. (2018) book equity BE is defined as shareholders' equity minus preferred stock. To obtain shareholders' equity, we use stockholders' equity (SEQ), but if it is not available, we use the sum of common equity (CEQ) and preferred stock (PSTK). If both SEQ and CEQ are unavailable, we proxy shareholders' equity by total assets (AT) minus the sum of total liability (LT) and minority interest (MIB). To obtain book equity (BE), we subtract from shareholders' equity the preferred stock value.

Following Campbell et al. (2008) to deal with any possible outliers, we adjust total assets by:

$$Total\ Assets\ (adjusted)_{i,t} = TA_{i,t} + 0.1\left(ME_{i,t} - BE_{i,t}\right).$$

Figure A1 – PTOs and the QMJ factor

This figure shows the time-varying feature of Quality as well as PTO waves from 1994 to 2023. More PTOs tend to occur in times when Quality is cheaper.

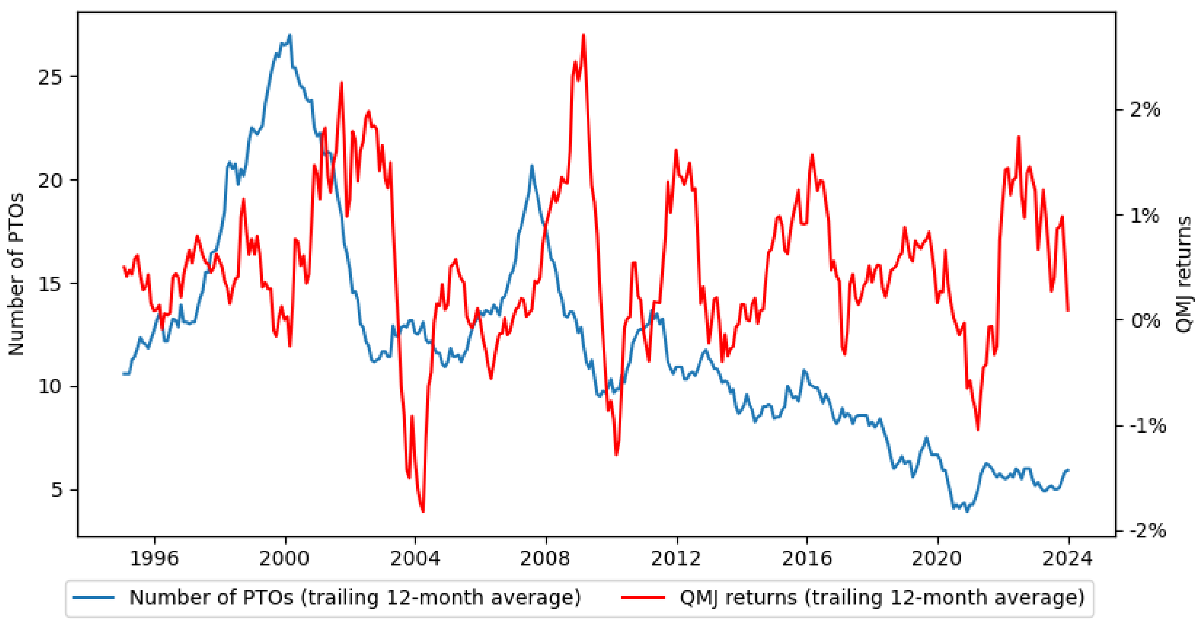

Table A1 – PTO and non-PTO factor returns

This table plots the PTO and non-PTO factor returns at the hypothetical PTO and non-PTO portfolio level. The Sharpe ratios are calculated as gross values.

		PTO portfolio - PTO factor returns				Non-PTO portfolio - Non-PTO factor returns			
Model	Metric	Top 25	Top 50	Top 75	Top 100	Top 25	Top 50	Top 75	Top 100
Base logit	Return	39.7 %	41.3 %	40.8 %	38.0 %	0.6 %	0.7 %	0.7 %	0.6 %
	Volatility	27.6 %	47.8 %	45.0 %	42.6 %	5.2 %	4.3 %	4.1 %	4.1 %
	G. Sharpe	4.98	3.00	3.14	3.08	0.40	0.53	0.57	0.51
	Weight	0.8 %	0.9 %	0.8 %	0.7 %	99.2 %	99.1 %	99.2 %	99.3 %
Base random forest	Return	36.9 %	34.3 %	33.6 %	34.1 %	-0.1 %	0.0 %	-0.1 %	-0.1 %
	Volatility	29.2 %	25.4 %	22.3 %	23.8 %	3.6 %	3.3 %	3.1 %	3.1 %
	G. Sharpe	4.38	4.69	5.21	4.96	-0.10	-0.04	-0.11	-0.11
	Weight	1.3 %	1.0 %	0.9 %	0.8 %	98.7 %	99.0 %	99.1 %	99.2 %
Enhanced combined forecast	Return	30.4 %	33.2 %	31.9 %	32.2 %	0.3 %	0.2 %	0.2 %	0.2 %
	Volatility	18.9 %	29.8 %	28.5 %	27.0 %	3.6 %	3.2 %	3.1 %	3.0 %
	G. Sharpe	5.56	3.86	3.88	4.14	0.26	0.24	0.24	0.19
	Weight	1.1 %	1.0 %	0.8 %	0.8 %	98.9 %	99.0 %	99.2 %	99.2 %

Figure A2 – Data structure for models

This figure shows the time structure of data used in running the PTO prediction models. All calculations are done at month-ends, implying that we know all data from the "current" month t. The models are trained on time-adjusted data trailing month t by 10 years. The predictions are calculated based on time-adjusted data from month t.