Does Transparency Increase Takeover Vulnerability?

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Keywords: Corporate Governance, Takeovers, Transparency, Stock Returns

JEL Classifications: G30, G34

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Abstract

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1 Introduction

Takeovers and especially models predicting takeovers have been of interest to academics and practitioners (see, e.g., Hasbrouck, 1985; Palepu, 1986; Ambrose, William, and Megginson, 1992). An important, recent study by Cremers, Nair, and John (2009) builds a baseline logit model with useful variables to measure takeover likelihood and documents that the takeover factor constructed using this model earns a positive risk premium. Another line of research on takeover vulnerability finds that external governance mechanisms improve valuations more strongly for transparent firms (see, e.g., Gu and Hackbarth (2013)). Therefore, this paper examines empirically whether transparency affects takeover vulnerability.

If higher transparency lowers uncertainty with respect to synergies and valuations of targets, then it should facilitate takeovers. This view is consistent with several studies in the accounting literature. For example, McNichols and Stubben (2015) show that acquiring firms' returns around merger announcements are higher when target firms have higher-quality accounting information, because acquiring firms can bid more effectively and pay less for their targets. Martin and Shalev (2017) find that firm-specific information about targets improves acquisition efficiency (measured by gains from merging). Therefore, we argue that a better information environment increases takeover vulnerability, such that it has an incrementally important impact on estimates of takeover likelihood.[1] To examine whether transparency affects takeover vulnerability, we construct a firm's takeover probability by augmenting the baseline logit model with three variables that measure a firm's transparency and compare the performance of our augmented model with the baseline model by studying the link between takeover probability and stock returns.

We adopt Dechow and Dichev's (2002) accrual quality as modified by McNichols (2002) as the primary proxy for transparency. We construct this measure as the standard deviation of residuals from an estimated model that regresses changes in working capital on cash

[1] See, e.g., Bushman, Piotroski, and Smith (2004) develop a framework of a firm's information environment that contribute to its transparency, defined as the availability of firm-specific information to those outsiders.

flows, changes in sales, and property, plant, and equipment. A lower standard deviation of the residuals indicates a better accrual quality as well as a more transparent information environment. We also investigate two alternatives to accrual quality: namely, forecast error and forecast dispersion based on analysts' earnings forecasts. In particular, we define forecast error as the absolute value of the difference between actual earnings per share and forecasted earnings per share, scaled by lagged stock price. Also, we defined forecast dispersion as as the standard deviation of earnings forecasts by analysts following the same firm in the same year, deflated by lagged stock price. A lower forecast error or a lower forecast dispersion implies higher transparency levels.

Importantly, transparency adds predictive power to the logit model for firms' takeover likelihood. Specifically, our augmented logit model enhances the estimation of takeover probability relative to the baseline model in various ways. First, when a transparency proxy is added, the logit estimation coefficient on this variable is negative and highly statistically significant without posing a significant impact on other variables' effects. Note that firm's transparency level decreases as the value of the proxy variable increases. Second, we find that the Pseudo-R^2 of the regression increases about 20%, providing supportive evidence that the augmented model fits the takeover data better. Third, we then construct firms' predicted takeover probability over the next year based on the logit estimation coefficients, and we compare the time-series of the average predicted takeover probability among firms in the top takeover probability decile with the time-series of the real takeover occurrence rate for the top decile. The curve for the predicted takeover probability matches the real takeover rate quite well, much more so than the curve for the predicted takeover probability that we form using the logit estimation results with the baseline model, because the correlation between the time-series of the predicted takeover likelihood and the real takeover rate are higher when we use our model.

To compare the performance of our newly constructed takeover likelihood with the takeover likelihood constructed using the baseline model, we follow Cremers, Nair, and

John (2009) to investigate the link between takeover likelihood and stock returns. We also find that firms with higher takeover likelihood are generally associated with higher stock returns over the sample period of 1991 to 2016. According to the predicted takeover likelihood, we sort firms into quintile or decile portfolios. The long-short portfolio that buys firms in the top takeover probability quintile and sells firms in the bottom quintile earns a monthly equal-weighted abnormal return of 86 basis points after we adjust for common risk factors. This monthly abnormal return increases to 134 basis points for the decile sorted long-short portfolio. Interestingly, the long-short portfolio that we form using our model generates higher average returns and abnormal returns than the long-short portfolio that we construct using the baseline model. For example, the mean return to the decile spread portfolio formed using the baseline model and our model is 118 basis points and 130 basis points, respectively. Although the difference is not remarkable, this pattern is true for all cases including the equal-weighted return, the value-weighted return, the decile sorted portfolio, and the quintile sorted portfolio. Our results not only confirm that takeover exposure is not idiosyncratic (i.e., carries a premium), but also reveal that our augmented model better captures a firm's real takeover exposure.

As our logit estimations and return calculations are over the same time period, an in-sample "look-ahead" bias of our results might occur, because the information might reflect the period after the realization of the return. To correct this bias, we re-estimate the logit model by using 10-year rolling windows. In other words, we construct the takeover probability in a year based on the logit coefficients that we estimate when we use all the observations during the preceding ten years; doing so ensures that a firm's information is incorporated into the market before the return calculation period. This out-of-sample estimation also confirms that firms with higher takeover probability are generally associated with higher stock returns. More important, we again find that the long-short portfolio that we form using our newly constructed takeover likelihood generates higher average returns and abnormal returns than the long-short portfolio that are constructed with the baseline takeover likelihood. These results indicate that the in-sample bias should not significantly impact our analysis in this paper.

We then construct a new takeover factor as the monthly return spread between the top quintile takeover likelihood portfolio and the bottom quintile takeover likelihood portfolio. To differentiate the pricing ability of our takeover factor from the baseline takeover factor, we also construct the baseline takeover factor in a similar fashion. Both takeover factors are able to bring the abnormal returns to the Fama-French 25 size and book-to-market sorted portfolios to a lower level after we account for only the market factor or all four common factors, which suggests a good pricing ability of both factors. Interestingly, including our takeover factor further reduces abnormal returns of the 25 portfolios in terms of magnitude and statistical significance. Although this improvement is not huge, our takeover factor performs better. Moreover, this fact holds true for both equal-weighted and value-weighted size and book-to-market sorted portfolios.

To access the premium associated with takeover exposure quantitatively with an additional test, we use 100 Fama-French size and book-to-market sorted portfolios to compute the takeover premium in two steps. We first calculate the portfolio beta on a specific factor as the loading on a particular factor in a multivariate regression of the excess return of each of the 100 portfolios on risk factors. We then calculate the premium associated with different factors as the coefficients from the multivariate regression of the mean excess return of each portfolio on all portfolio betas. Notably, the premium associated with the augmented takeover factor is higher than the premium associated with the baseline takeover factor when the Carhart four-factor model, the Fama-French three-factor model, or the capital asset pricing model (CAPM) are employed as benchmark models. This reinforces the result that our logit model better captures potential takeover vulnerability.

Our study contributes to the literature in several ways. First, our paper is the first to propose and provide empirical evidence to support the view that firm's information environment is an important determinant of its takeover likelihood, which has been studied extensively over the past several decades (e.g., Palepu, 1986; Stulz, 1988; Ambrose and Megginson, 1992; Shivdasani, 1993; Chaplinsky and Niehaus, 1994; Mitchell and Mulherin, 1996; Field and Karpoff, 2002; Dong, Hirshleifer, Richardson, and Teoh, 2006; Dessaint, Golubov, and Volpin, 2017). We offer a new empirical model to predict firm's takeover likelihood and this augmented model performs better than the baseline model in various ways. Second, our paper complements and extends recent research in accounting on the role of target firms' information quality on mergers and acquisitions. McNichols and Stubben (2015) find that target firms accounting quality positively affects acquiring firms returns around merger announcements. Marquardt and Zur (2015) shows that financial accounting quality affects the reallocation of resources in the market for corporate control. Martin and Shalev (2017) shows that firm-specific information about targets improves acquisition efficiency. Our findings are consistent with these studies in that higher transparency can facilitate takeovers. Third, our paper also adds to the corporate governance literature. Recently, Gu and Hackbarth (2013) find that transparent firms benefit more from good governance (as measured by a low number of anti-takeover provisions). If transparent firms are associated with higher takeover likelihood, their good governance mechanism should be more effective.[2]

The rest of our paper proceeds as follows. In Section 2, we outline our data sources, variable definitions, and summary statistics. In Section 3, we provide our logit estimation results of takeover likelihood and investigate the relation between takeover probability and stock returns. In Section 4, we construct a new takeover factor and use size and book-to-market portfolios as base assets to test its cross-sectional pricing performance; we present comparisons between our augmented model and the baseline model throughout Sections 3 and 4. Finally, we conclude this paper with Section 5.

[2]On a similar note, Armstrong, Balakrishnana, and Cohen (2012) document that when a firm's external governance weakens, its information environment improves; however, they do not study takeover probabilities or stock returns.

2 Data Sources and Variables

2.1 Data sources

Throughout this paper, we employ three main data sources: the Securities Data Corporation's (SDC) database, which provides information for merger and acquisition cases; the North America Compustat Annual Files (COMPUSTAT), which contain firm-level accounting data; and the Center for Research in Security Prices (CRSP) database, from which we obtain monthly stock returns data. Following Cremers, Nair, and John (2009), we only consider all completed or 100% completed takeover deals from the SDC database in our analysis, and we also include both friendly and hostile deals.[3] 100% completed takeovers refer to deals for which 100% of the target is acquired. After matching the SDC database with COMPUSTAT, we obtain a sample of 3,166 takeover targets with non-missing estimation variables if we use all completed deals over the time period from 1991 to 2016, and this number decreases to 2,628 takeover targets if we use 100% completed takeovers only.[4]

We also use several other data sources in our empirical analysis. For example, we obtain monthly observations for the standard Fama-French risk factors and monthly average returns to test different portfolios from Kenneth French's website; we also obtain quarterly institutional (13F) holdings data from Thompson/CDA Spectrum to construct institutional ownership.

2.2 Measures for Transparency

Our main measure for a firm's transparency level is accrual quality (or shortly, AQ). Following McNichols (2002) (see also Dechow and Dichev, 2002; Francis, Olsson, and Schipper, 2008; McNichols and Stubben, 2015), we construct accrual quality as the standard deviation

[3]Because the chance of completion of a hostile takeover is low, the number of hostile completed deals in the sample is small. Dropping hostile deals from the sample does not affect our logit estimation results.

[4]The construction of the transparency variable involves estimations over longer time windows. To ensure non-missing transparency variables, our sample starts in 1991. Otherwise, the sample period can begin with 1981.

of residuals from the following estimated model:

$$\Delta WC_t = b_0 + b_1 CFO_{t-1} + b_2 CFO_t + b_3 CFO_{t+1} + b_4 \Delta Sales_t + b_5 PPE_t + \epsilon_t, \qquad (1)$$

where ΔWC_t is the change in working capital from year $t-1$ to year t. Specifically, it is computed as the increase in accounts receivable plus the increase in inventory minus the increase in accounts payable and accrued liabilities minus the increase in taxes accrued plus the increase (decrease) in other assets or liabilities. CFO is operating cash flow, $\Delta Sales_t$ is change in sales from year $t-1$ to year t, and PPE is property, plant, and equipment. We scale all variables by lagged total assets. For each year, we estimate this model for every firm by using data of the prior twelve years, and we define the standard deviation of residuals as accrual quality.[5] A larger standard deviation indicates lower accrual quality, lower transparency, and higher opacity.

We consider alternative transparency measures by using analysts' earnings forecasts from the Institutional Brokers' Estimates System (I/B/E/S). Based on the I/B/E/S data, we construct two transparency proxies: forecast error and forecast dispersion. In particular, we define forecast error as the absolute value of the difference between actual annual earnings per share and average analyst forecasts. Also, we define forecast dispersion as the standard deviation earnings forecasts across all analysts following the same firm in the same year. These two variables are all standard in the literature and are frequently used by researchers in accounting and finance.[6] To make these measures of transparency comparable across firms, we deflate them by lagged stock price.[7] Also, to ensure the reliability of these measures, we require that at least three different analysts provide forecasts for a given firm during the year. To limit the influence of coding errors and outliers, we winsorize forecast error or forecast dispersion at the 1% and 99% percentile of their empirical distributions.[8]

[5] The results do not change qualitatively, when we estimate the model by using data of the prior eight or ten years.

[6] See, e.g., Givoly and Lakonishok (1979), Lang and Lundholm (1996), Thomas (2002), and Zhang (2006).

[7] When we deflate those variables by forecast mean or total assets, we obtain qualitatively similar results.

[8] Some papers remove observations for which forecast error is larger than 10% of the share price at the beginning of the fiscal year to limit the influence of outliers (e.g., Easterwood and Nutt, 1999; Lim, 2001;

The "transparency" concept in this paper is quite standard — it follows Bushman, Piotroski, and Smith (2004) — in that it is how much information is available to outsiders and this can be affected by, e.g., (1) how much information is disclosed by the firm and the quality of the information and (2) information acquisition and aggregation from public and private sources by intermediaries. According to Bushman, Piotroski, and Smith (2004) who study the determinants of corporate transparency, quality of corporate reporting is an important dimension of transparency and accrual quality (our main measure for transparency) is commonly used in accounting and finance to capture this dimension. Our two alternative measures for transparency, forecast error and forecast dispersion, are frequently employed to measure analysts' information acquisition and digestion which can be affected by firms' complexity. Thus, complexity can actually affect how much information is available for outsiders and complex firms tend to be one type of "opaque" firms. Therefore, even though firms' complexity might lead to higher analyst forecast error and forecast dispersion, this does not affect the interpretation of our results about "transparency".

2.3 Summary statistics

Our logit model for estimating a firm's takeover probability involves several independent variables that are defined as follows: Q is the ratio of the market value of assets to the book value of assets, and we compute the market value of assets as total assets plus the market value of common stock minus the sum of the book value of common equity and differed taxes. PPE is property, plant, and equipment scaled by total assets. $Cash$ is the ratio of cash and short-term investments to total assets. $Size$ is measured by the natural logarithm of firm's market capitalization. $Leverage$ is the book value of debt scaled by total assets. ROA is the return on assets. $Industry$ is a dummy variable that equals one, if in the previous year, there was at least one takeover event in the firm's industry, as defined based on Fama-French 48 industry classifications, and zero otherwise. $Block$ is also a dummy variable that equals

Teoh and Wong, 2002; Giroud and Mueller, 2011). Our results are qualitatively similar if we adopt this procedure.

one if there is at least one institutional owner whose ownership stake in a firm's outstanding shares exceeds 5%, and zero otherwise. We construct this variable by using the quarterly institutional (13F) holdings data from Thompson/CDA Spectrum.

[Insert Table 1 Here]

Table 1 presents summary statistics for the independent variables that we use in our logit estimation. Specifically, we provide the mean values of those variables for both non-target and target firms over the period from 1991 to 2016, so we may see how these two groups differ with respect to the means of those variables. As we show in Table 1, for the sample that includes all completed takeovers, almost all variables for the target group are significantly different from those for the non-target group, with the exception of ROA. For example, the mean of Q for the target group is 1.938, while the mean of Q for the non-target group is 2.560, and the difference of the mean is highly statistically significant with a t-statistic of 5.14. This finding makes intuitive sense, because acquirers are more likely to be the ones that have high valuations and seek good investment opportunities. While the mean of $industry$ for the target group is 0.940, it is 0.885 for the non-target group, and the difference between them is also significant with a t-statistic of 16.24. This result is in line with the fact that takeovers are likely to be industry clustered. The average difference of $BLOCK$ is also highly significant with the target group having a higher average level of institutional ownership. This finding is consistent with Cremers and Nair (2005), who argue block holders can facilitate takeovers.

Since a higher value of accrual quality, forecast error, or forecast dispersion means either a lower level of transparency or a higher level of opacity, to facilitate the interpretation of our test results, we denote these transparency proxies as *Opacity* in later sections. In Table 1, *Opacity* is the accrual quality estimated according to McNichols (2002). Importantly, the mean difference of *Opacity* is highly statistically significant with the target group having a lower value than the non-target group. Specifically, the mean for the target group is 0.023, and the mean for the non-target group is 0.029. The t-statistic for the mean difference is 12.01. This finding is consistent with the main message we would like to convey that transparency can facilitate takeovers. In sum, our summary statistics in Table 1 provide important information that potentially identifies crucial determinants of the probability that a takeover event may occur, and this information will be reflected in our logit estimation results in the following section.

3 Takeover Probability

In this section, we use an augmented logit model to estimate firms' takeover probability in the next year and study the relation between takeover exposure and firms' equity return by computing the returns to the quintile or decile portfolios constructed based on a firm's predicted takeover likelihood which is formed using the coefficients from the logit estimation. We compare and contrast the results from our model with the results from the baseline model to test the augmented impact of the new variable, *Opacity*, on the prediction of takeover likelihood.

3.1 Logit estimation

The summary statistics in Table 1 show that target firms have a number of characteristics that are different from non-target firms. However, the table does not inform us about whether these variables interact to improve takeover probability predictions. Following Cremers, Nair, and John (2009) and others, we employ a logit model to estimate the probabilities of being taken over in the next period. We assume that the marginal probability of becoming a target over the next period follows a logistic distribution and is given by the following equation:

$$\Pr(T_{it} = 1) = \frac{1}{1 + \exp(-\alpha - \beta X_{it-1})}, \tag{2}$$

where T_{it} is a dummy variable that equals one if the firm is a target in year t, and X_{it-1} is a vector of explanatory variables known at the end of the previous year. The elements of X_{it-1} include Q, PPE, $Cash$, $Size$, $Leverage$, ROA, $Industry$, $Block$, and $Opacity$; we provide detailed definition of these variables in the data section. All these variables except *Opacity* have been used by researchers in prior studies to understand and predict takeover events (see, e.g., Ambrose and Megginson, 1992). We augment the model by adding *Opacity* as an additional predicting variable since several articles in the literature show that firms' transparent environments can facilitate takeovers, because acquiring firms can bid more effectively and the expected synergies are larger for target firms that are more transparent (see, e.g., McNichols and Stubben, 2015; Martin and Shalev, 2017). Thus, transparent firms are more attractive targets, and takeover attempts are more likely. COMPUSTAT variables are industry adjusted by subtracting the median value of the empirical distribution from the data. We also include year dummy variables in our logit regression to account for time-fixed effects.[9]

[Insert Table 2 Here]

We estimate the logit model once by using all the observations from 1991 to 2016, and we report our regression results in Table 2.[10] Model 1 refers to the baseline logit model used in prior studies, and Model 2 refers to the augmented model with all the variables included in Model 1 and the additional predicting variable, *Opacity*. For both models, we report the estimation coefficients for each variable. As shown, when we use Model 1, the coefficients on the variables Q (the market-to-book ratio), *Block* (more than 5% ownership stake dummy), *Industry* (the dummy variable to capture the clustering of takeover activity within an industry), and *Size* are highly statistically significant.[11] These findings reveal that target firms tend to have low market-to-book ratio, high institutional ownership, and small size, and these firms are likely in industries with takeover occurrence in the previous year. These findings all support those found in prior studies in the literature. However, the coefficients on *ROA* and *Leverage* are significant but positive. This is perhaps surprising, because firms with low leverage or low returns on assets could be taken over more easily.

[9] When we estimate the model without year dummy variables, our results are similar.

[10] The estimation of accrual quality requires rolling window regressions. Reliable values of this transparency measure can only be formed as early as 1991.

[11] The unreported p-value of those coefficients are less than 0.0001.

Such firms could be more likely targets given that deals involve fewer issues with debt holders and greater potential to improve performance if low returns reflect inefficient management. Nevertheless, this finding is consistent with prior studies in the literature, which also show positive signs associated with these variables, albeit sometimes with different samples. Thus, these two variables seem to not have persistent predicting power of takeover probability.[12]

Model 2 refers to the augmented model with all the variables included in Model 1 and the variable of our interest, *Opacity*. Notably, when we use Model 2, the coefficient on *Opacity* is negative and highly statistically significant. Specifically, when we use the sample with all completed deals, the coefficient on *Opacity* is -5.431 with a t-statistic of 6.56. This finding indicates that transparent firms have higher predicted takeover probability than opaque firms, all else equal. In fact, adding this additional variable does not diminish the effects of other variables, and the coefficients on the variables that we include in Model 1 remain highly significant with similar magnitude. For example, the coefficient on the variable, *Industry*, is 0.567 (t-statistic = 6.77) in Model 1 and it increases to 0.592 with a t-statistic of 7.06 in Model 2. The coefficient for the variable, *Block*, is 0.664 (t-statistic = 14.02) in Model 1 and is 0.653 with a t-statistic of 13.79 in Model 2. However, the magnitude of the coefficient on Q decreases and the magnitude of the coefficient on *Size* increases slightly from Model 1 to Model 2, perhaps because there is a correlation between *Opacity* and these two variables. More specifically, adding the new variable does not change the effects of the variables in the baseline model. Thus, the results in this table confirm our hypothesis that transparency can facilitate takeovers and, hence, it should be another dimension that can affect firms' probability of being taken over in the next time period.

To see how the models fit the takeover data, we also report the Pseudo-R^2 for each estimation at the bottom of Table 2. We note that augmenting the baseline model with the *Opacity* variable raises the level of Pseudo-R^2 to some extent.[13] For example, when we

[12]When we use market leverage to replace book leverage, we find that the sign of leverage flips from positive to negative only occasionally; thus, the predictive power of leverage is not so persistent.

[13]Cremers, Nair, and John (2009) reports a Pseudo-R^2 of 1.39% using Model 1 with a sample of all

use the sample with 100% completed deals, the Pseudo-R^2 increases from 3.78% in Model 1 to 4.60% in Model 2. This increase is about 20% of the original value, indicating that the augmented model should fit the data better and have additional predicting power of the takeover likelihood.

To examine whether our results are robust when we use different measures of transparency, we also provide estimates for Model 2 in Table 2 for alternative transparency proxies—forecast error and forecast dispersion—that are constructed based on analysts' earnings forecasts. Specifically, we define forecast error as the absolute value of the difference between actual annual earnings per share and average analyst earnings forecasts. Also, we define forecast dispersion as the standard deviation of earnings forecasts across all analysts following the same firm in the same year. Intuitively, lower levels of forecast error and forecast dispersion imply higher levels of transparency, because if a firm is transparent, which means there is more information available to firm outsiders, analysts tend to generate more accurate and less dispersed earnings forecasts. We scale these variables by lagged stock price to ensure comparability across firms.[14] In Table 3, we report our logit estimation results when we use Model 2 over the sample period of 1991 to 2016.

[Insert Table 3 Here]

Our estimation results in Table 3 are consistent with our previous findings. Put differently, the coefficients on the transparency measures are statistically significant for both proxies—forecast error and forecast dispersion—and adding the new variable does not diminish the effects of other variables. Specifically, the coefficient for forecast error is –0.721 and is statistically significant at the 1% level. The coefficient for forecast dispersion is –0.914 with a t-statistic of 4.29. Notably, the Pseudo-R^2 also increases from Model 1 to Model 2. For example, the Pseudo-R^2 is 3.53% for the logit estimation with Model 1 and increases to 4.45% when we augment the baseline model with the transparency measure, forecast error.

completed deals from 1981 to 2004.

[14]These variables are all standard in the literature and are frequently used by researchers in accounting and finance.

We detect a similar pattern when we employ forecast dispersion to gauge a firm's transparency level. The Pseudo-R^2 increases to 4.47% in Model 2. Therefore, the test results in Table 3 provide additional supportive evidence that firms' transparent environments do have additional predicting power on firms' future takeover probability.

To further examine the predictability of the augmented model, we compare the predicted takeover likelihood with the realized takeover event rate. To compute firms' predicted takeover likelihood, we use Equation (2) and the logit estimation coefficients from Model 2 in Table 2. Each year, firms are sorted into deciles or 20 equal-size groups based on the value of their predicted takeover probability. The real takeover event rate is calculated within each group every year as the number of takeovers deflated by the total number of firms in that group. In Table 4, we report the mean value of the predicted takeover likelihood and the realized takeover event rates over the sample period of 1991 to 2016. For comparison's sake, we also perform the same analysis by using Model 1 to compute the predicted takeover probability, and we report these statistics in the right part of each panel in Table 4.

[Insert Table 4 Here]

In Panels A and B, we show the results for decile portfolios and 20 equal-size portfolios, respectively. As shown in the right part of Panel A, when we use Model 2, the realized takeover rate is increasing monotonically with the predicted takeover likelihood. Specifically, the real takeover rate goes from 0.0095 in decile 1 to 0.0524 in decile 10, and the predicted takeover likelihood goes from 0.0115 in decile 1 to 0.0541 in decile 10. The correlation between the average predicted takeover likelihood and the realized takeover rate is as high as 0.97. We find a similar pattern in the right part of Panel B for 20 equal-size portfolios. The real takeover rate increases monotonically from 0.0056 in group 1 to 0.0523 in group 20, and the predicted takeover probability goes from 0.0093 in group 1 to 0.0582 in group 20. The correlation between these two measures is 0.95. Thus, our results show that there are actually more takeover activities among firms with higher predicted takeover probabilities, which reveals a remarkable predictive power of the augmented logit model.

In the left part of Table 4, we report our results when we calculate the takeover probability by using the estimation coefficients from the baseline logit model (Model 1 in Table 2). We find that the predicted takeover likelihood generally follows the trace of the realized takeover event rate from decile 1 to decile 10 or from group 1 to group 20. For example, the realized takeover rate is 0.0104 in decile 1 and increases to 0.0495 in decile 10, and the corresponding predicted takeover probability is 0.0122 in decile 1 and 0.0523 in decile 10. However, the correlation of these two measures is 0.95 for decile portfolios and is 0.92 for 20 equal-size portfolios. These correlation values are lower than the corresponding values when we use Model 2 as the takeover predicting model. Therefore, the results we present in Table 4 provide supportive evidence that the augmented model can actually fit over 25 years of real takeover data quite well; thus, transparency represents an additional and crucial dimension of takeover event predictions.

Table 4 shows how fit the model is with the predicted takeover likelihood averaged over the sample period. However, an investigation of the relation between the predicted takeover likelihood and the real takeover rate over time would provide more valuable information. Thus, in Figure 1, we plot the time-series of the average predicted takeover probability and the real takeover rates for the top decile group (i.e., the decile with the highest level of predicted takeover likelihood) over the sample period of 1991 to 2016.[15] Because the real takeover rate here is computed among firms with full logit estimation information, this particular rate is slightly different from the actual takeover rates. As we show in Figure 1, the real takeover activity shows an up-trend in the 1990s and then decreases in the early years of the 21st century, only to rise again until the start of the financial crisis. Although the time-series of the predicted takeover probability is less volatile than that of the actual takeover activity, it generally follows its trace fairly well, and the correlation between these two series

[15]The graph for other decile groups are also plotted, but not displayed here. All undisplayed graphs show reasonably good predictability of the real takeover activity by the predicted takeover likelihood.

is as high as 0.76. Thus, the predicted takeover probability can capture a reasonably large part of the variations of the realized takeover activity over time.

[Insert Figure 1 Here]

For comparison's sake, we also plot the graphs when we compute the predicted takeover likelihood using the estimation coefficients from the baseline model (Model 1). As we show in part two of Figure 1, the predicted takeover likelihood curve generally follows the path of the realized takeover rates over time, yet this curve does not capture the details of the real takeover activity as well as the time-series of the predicted takeover probability constructed using the augmented model (Model 2). This is also reflected in the correlation between these two series. In this case, the correlation is 0.59, which is lower than the correlation of the two time-series in part one of Figure 1.

Overall, these test results show that augmenting the baseline model with transparency variables produces a better fit for the real takeover data. Specifically, the augmented model shows better performance than the baseline model since it produces higher Pseudo-R^2 for the logit estimation and a larger correlation between the time-series of the average predicted takeover probability and the realized takeover rate.

3.2 Returns to takeover probability portfolios

Several articles in the literature (e.g., Bruner, 2004) show that firms face systematic exposure to takeover activities which are related to market conditions and this exposure should have significant impact on firms' value and stock returns. Cremers, Nair, and John (2009) is the first article that studies the link between takeover likelihood and equity returns. Our previous empirical results show that augmenting the baseline model with the transparency variable provides a better estimate of firm's takeover likelihood. To examine how this improvement affects the relation between takeover likelihood and equity returns, we adopt the standard portfolio sorting approach.

Specifically, we use the logit estimation coefficients from our augmented model (Model 2) to compute the probability of being taken over in the next year by using Equation (2) and then sort firms into quintile or decile portfolios every year, according to the rank of their takeover likelihood. Monthly equal-weighted quintile portfolio returns as well as equal-weighted and value-weighted returns to the long-short portfolio that holds a long position in firms with high takeover probability and a short position in firms with low takeover probability are reported in Table 5. For comparison's sake, we also report the returns to the long-short portfolio constructed based on the takeover likelihood estimated with the baseline model (Model 1) at the bottom in each panel.

To investigate whether portfolio returns can be captured by existing standard risk factors, we also use the Carhart (1997) four-factor model to adjust for different risk styles of the takeover probability-sorted portfolios. If the takeover-probability sorted portfolios simply reflect different combinations of the loadings on those existing factors, we would not expect any significant abnormal returns. In Table 5, we also report the abnormal portfolio returns (alphas), together with their statistical significance levels.

[Insert Table 5 Here]

In our logit estimation in Table 2, we use all the observations over the period of 1991 to 2016 to compute the variable coefficients, and our return calculations in this section also reflect the same time period. As a result, we note that an in-sample "look-ahead" bias might occur, because the information might reflect the period after the realization of the return. To correct this bias, we re-estimate the logit model using 10-year rolling windows.[16] For example, we would calculate takeover probability in year 2001 using the logit estimation coefficients that reflect all observations from 1991 to 2000. However, this out-of-sample estimation also has limitations. For example, the data requirements shorten the portfolio return

[16]To ensure that we include enough target observations in the logit estimation, we choose the 10-year rolling window for the logit estimation. Too short of a window will result in unstable and unreliable logit estimation results (noise), and too long of a window will leave us with only several years of rolling takeover probability estimation (bias).

calculation periods by ten years, which could also cause potential bias. For comparison's sake, we also tabulate results using the 10-year rolling window estimation and present these results in the right part of Table 5.

Consistent with the literature, we also find a positive relation between the newly constructed takeover likelihood and stock returns. As shown in Panel A, both mean return and abnormal return to the takeover likelihood sorted portfolio generally increase from quintile 1 to quintile 5, and the hedge portfolio that buys stocks with high takeover likelihood and sells stocks with low takeover likelihood earns an equal-weighted abnormal return of 86 basis points per month; this finding is highly statistically significant (t-statistic = 5.74). Not surprisingly, the equal-weighted abnormal return to the long-short decile portfolio is higher with 134 basis points per month and a t-statistic of 6.69.

We find our results are similar when we use the takeover probability computed from the 10-year rolling window logit estimation. In this case, the information used to construct the takeover likelihood is prior to the return period, and the "look-ahead" bias is corrected. The monthly abnormal return, α, to the long-short quintile portfolio is 0.71% with a t-statistic of 4.90 and is 1.29% with a t-statistic of 5.21 for the long-short decile portfolio. Thus, this out-of-sample test also confirms the positive relation between our newly constructed takeover likelihood and stock returns. We also report the value-weighted alpha for the long-short portfolios, but the results are a bit weaker in terms of magnitude and statistical significance.[17]

The returns to the long-short portfolios when we use the baseline model (Model 1) to estimate takeover probability are also reported at the bottom of Table 5 for comparison's sake. As shown, return spreads and four-factor alphas here are smaller than the return spread and the four-factor alphas when we use the augmented model (Model 2) to compute takeover probability. For instance, the equal-weighted return to the long-short decile portfolio is 118 basis points per month, which is 12 basis points lower than the return spread when Model 2 is used. In the value-weighted case, the return spread is 1.13% and 0.91% when Model 2

[17] Cremers, Nair, and John (2009) also find weaker value-weighted results.

and Model 1 are used, respectively. Also, the equal-weighted four-factor alpha is 1.34% for Model 2 and is 1.22% for Model 1, and the value-weighted four-factor alpha is 0.83% and 0.63%, respectively. Overall, these findings indicate that the relation between firms' takeover likelihood and stock returns is actually stronger when we measure the takeover likelihood more precisely with our augmented model.

[Insert Figure 2 Here]

To track the return performance of the takeover probability sorted portfolio over time and compare it between Model 1 and Model 2, we compute the cumulative return to the long-short portfolio each year. In Figure 2, we illustrate the performance of the long-short portfolio that buys firms with top levels of takeover likelihood and sells firms with bottom levels of takeover likelihood over the sample period of 1991 to 2016. We then sort firms into either quintiles or deciles to plot the time-series of the cumulative monthly returns of the long-short portfolios, which are, respectively, "LS2080" and "LS1090" in this graph. As shown, the performance of all long-short portfolios is remarkably consistent over time. Specifically, in most years across the 1990s and the 2000s, there are positive return spreads, with the most negative returns concentrated in a few years in the late 2000s. Furthermore, the curves for the long-short portfolios when we form takeover probability based on the logit estimation results from Model 1 are always below the corresponding curves from Model 2, confirming our portfolio sorting results that the takeover premium is stronger when you can capture the takeover likelihood more accurately.

To summarize, the results in this section extend Cremers, Nair, and John (2009), who also find a positive relation between the likelihood of being taken over in the next period and average stock returns. Notably, we augment their model with an incrementally important variable that has significant predictive power for takeovers. The long-short portfolio formed based on the logit estimation results from the augmented model generates larger return spreads than the long-short portfolio constructed based on the results from the baseline model. This finding implies that the premium associated with takeover exposure can be larger if we more precisely proxy for takeover vulnerability.

4 Takeover Factor

Cremers, Nair, and John (2009) show that the takeover factor created based on the baseline logit model has pricing power for certain base assets. Since the return spread when we use the augmented model is larger than when we use the baseline model, it would be interesting to see whether the takeover factor constructed based on the augmented logit model is more effective in pricing the cross-section of stock returns. Thus, in this section, we create a new takeover factor and test its performance using 25 Fama-French size and book-to-market sorted portfolios as base assets. We also compute the premium associated with both the baseline takeover factor and the augmented takeover factor using 100 Fama-French size and book-to-market sorted portfolios.

4.1 Construction of the takeover factor

Our takeover factor (TOP) is the monthly equal-weighted portfolio return to the long-short portfolio that buys firms with the top takeover likelihood and sells firms with the bottom takeover likelihood. In Table 6, we present summary statistics of the TOP factor along with four common factors, i.e., MKT, SML, HML, and UMD. ($TOPO$ will be the baseline takeover factor.)

[Insert Table 6 Here]

Panel A contains some basic statistics of these five factors. The average monthly return of the takeover factor from 1991 to 2016 is 0.76% (t–statistic = 3.33), which confirms our previous results that there is a significant premium associated with takeovers over the sample period. Panel A also offers two additional findings. First, the mean of the TOP factor is higher than other factors over our sample period. Second, the TOP factor is almost as volatile as the market, the size, and the book-to-market factors. Panel B lists the correlation matrix of these factors. The takeover factor is negatively correlated with the momentum factor with a correlation coefficient of –0.20, and this factor has a positive correlation of 0.33 with the size factor. This finding is consistent with our logit estimation results that smaller size firms tend to have higher takeover likelihood. Intuitively, it requires less resource for the potential bidder to take over a small size firm. The new takeover factor is also positively correlated with the value factor with a correlation coefficient of 0.15.

4.2 Pricing 25 Fama-French size and book-to-market Portfolios

Next, we test the performance of our takeover factor using 25 Fama-French size and book-to-market portfolios as the base assets. Specifically, we estimate the following asset pricing models:[18]

$$R_t - R_f = \alpha + \beta_1 \times RMRF_t + \epsilon_t, \tag{3}$$

$$R_t - R_f = \alpha + \beta_1 \times RMRF_t + \gamma \times TOP_t + \epsilon_t, \tag{4}$$

$$R_t - R_f = \alpha + \beta_1 \times RMRF_t + \beta_2 \times SMB_t + \beta_3 \times HML_t + \beta_4 \times UMD_t + \epsilon_t, \tag{5}$$

$$R_t - R_f = \alpha + \beta_1 \times RMRF_t + \beta_2 \times SMB_t + \beta_3 \times HML_t + \beta_4 \times UMD_t + \gamma \times TOP_t + \epsilon_t, \tag{6}$$

where $R_t - R_f$ is the excess return of the portfolio. We compare the regression intercept α and its t–statistic using these four models. Given that α represents the estimate of the expected excess returns unexplained by the risk factors in the asset pricing model, any amount of decrease in the magnitude or the statistical significance of α can indicate an improved performance of the model.

[Insert Table 7 Here]

In Table 7, we shows the mean excess return and the abnormal returns of the 25 size and book-to-market equal-weighted portfolios adjusting for risk factors using different asset

[18] The data set for the 25 portfolio returns comes from Kenneth French's website.

pricing models. In Panel A, we report the equal-weighted monthly mean excess return and the corresponding t-statistics are reported in Panel A as the benchmark to test the performance of different models. In Panels B and D, where we use either the market-factor or the four-factor model, the excess return is reduced to some extent. Comparing Panel B with Panels C to E, we observe that augmenting the single-factor or four-factor models with our takeover factor further reduces the alphas of both models in terms of magnitude and statistical significance. For example, for the smallest size and highest book-to-market portfolio, the monthly alpha goes from 0.78% to 0.09% and the t-statistic goes from 4.76 to 0.69 when we include the augmented takeover factor in the four-factor model. This result suggests that the takeover factor has its own pricing power independent of the common risk factors. We present the test results with 25 value-weighted size and book-to-market portfolios in Table A1 in the Appendix, and we draw similar conclusions from the results.

To investigate whether the augmented takeover factor constructed using the augmented model performs better than the baseline takeover factor formed based on the baseline model, we also construct the baseline takeover factor over our sample period using the estimation results of Model 1 in Table 2. We estimate an alternative five-factor model that includes the baseline takeover factor to compare its pricing properties to the five-factor model that includes our augmented takeover factor. Table 8 presents the estimation results for the 25 equal-weighted size and book-to-market portfolios.

[Insert Table 8 Here]

For comparison's sake, we report as benchmark returns the mean excess return and the Carhart (1997) four-factor alpha for the 25 portfolios in Panel A and Panel B, respectively. Panel C shows the abnormal returns adjusting for the five factors, including the market factor, the size factor, the value factor, the momentum factor, and the augmented takeover factor. Panel D represents the abnormal returns of the five-factor model that instead uses the baseline takeover factor. We identify the augmented takeover and the baseline takeover factors as TOP and $TOPO$, respectively. Comparing the abnormal return alphas in Panel C with those in Panel D, we can see that the corresponding alphas from both panels are of comparative magnitude, with the model in Panel C having better performance for some portfolios. For instance, for the smallest size and highest book-to-market portfolios, the monthly four-factor alpha is 0.78% (t-statistic = 4.76), the five-factor model including the TOP factor lowers the value of this alpha to 0.09% (t-statistic = 0.69), while the five-factor model with the $TOPO$ factor produces an alpha of 0.21% with a higher t-statistic of 1.43. For many other portfolios, the differences between the abnormal returns and the t-statistics in Panel C and Panel D are small; however the five-factor model including the augmented takeover factor produces smaller or equal value alphas and t-statistics. Thus, the augmented takeover factor does have better pricing performance for the 25 equal-weighted size and book-to-market portfolios than the baseline takeover factor.

In Table A2 in the Appendix, we present the results for the 25 value-weighted size and book-to-market portfolios. Similar insights can be obtained from this table. For example, when we compare the alphas in Panel C with the alphas in Panel D, we observe that the five-factor model with the augmented takeover factor reduces the four-factor alpha to a lower level in some cases than the five-factor model with the baseline takeover factor, although the magnitude of the difference is small. For instance, for the smallest size and highest book-to-market portfolios, the five-factor alpha is 0.08% when we employ the baseline takeover factor ($TOPO$) in the five-factor model and is –0.01% when we use the augmented takeover factor (TOP). The corresponding t-statistics are 1.20 and 0.09, respectively. Although the difference is not significant, the performance of the augmented takeover factor is still better. Thus, the results from these two tests reveal that our takeover factor better captures variations in the cross-section of stock returns, reinforcing our main finding that transparency contributes incrementally helpful predictive power to the baseline model of takeover likelihood.

4.3 Premium associated with the takeover exposure

The results in previous tables show that the return spread of the long-short takeover probability portfolio is larger when we use our augmented model in the logit estimation. This implies a larger premium associated with takeover exposure. To access this premium quantitatively, we use the 100 Fama-French size and book-to-market portfolios as base assets for this test.

Implementing this test involves two steps. First, we obtain the beta of each of the 100 portfolios by regressing the excess return of each of the 100 portfolios on risk factors, and we consider the loading or regression coefficient on the factor to be the beta of the portfolio associated with that particular factor. We then obtain the premium associated with each factor as the coefficient of the regression of the mean excess return of those 100 portfolios on all portfolio betas. We next compute betas for both the augmented takeover factor and the baseline takeover factor. Finally, we compare premiums associated with these two factors. In Table 9, we display our results.

[Insert Table 9 Here]

Panel A shows the coefficients when we use the Carhart (1997) four-factor model as the benchmark model. As shown in the first two columns in Panel A, all factors are priced, which is consistent with findings in the literature. When the takeover factor constructed using the baseline model is added to the regression, the coefficients on the other four factors only have slight changes, and there is a significant premium associated with the takeover factor over the sample period. Specifically, the annualized coefficient on the baseline takeover factor is 5% with a t-statistic of 4.78. This finding suggests that the premium for takeover exposure can be as high as 5% annually.[19] Notably, when we replace the baseline factor by the augmented takeover factor in the third regression of Panel A, this premium rises to 6% (t-statistic = 5.51) annually, which corresponds to a 20% increase.

[19]Cremers, Nair, and John (2009) also reports 8% annual premium associated with the takeover factor constructed using the same logit model over the period of 1981 to 2004.

To check for robustness, we also perform similar tests with the Fama-French three-factor model and the single-factor (market) model as benchmarks, and we report our results, respectively, in Panels B and C of Table 9. Recall that Table 6 shows that correlations between the takeover factor and other common factors are high. Thus, using the CAPM to perform the tests again ensures that our results in Panel A of Table 11 are not driven by correlations between these factors. In Panel B, the coefficient estimate on the baseline takeover factor also is 5% and significant (t-statistic = 5.31). However, the takeover premium goes up to 7% with a t-statistic of 5.59 if we use the augmented takeover factor. Notice that a similar pattern prevails in Panel C, where the takeover premium increases by two percentage points when we move from the baseline takeover factor to the augmented takeover factor (i.e., from 3% to 5%). Because these robustness tests deliver larger changes in takeover premiums, they lend further support to the finding in Panel A.

We also report the R^2 of each regression at the bottom of each panel. Observe that, in Panel A, the R^2 increases from 38% to 45% when we include the baseline takeover factor in the regression. More importantly, when we replace it by the augmented takeover factor, the fit further improves in that the R^2 rises from 45% to 53%. The TOP factor hence produces a significant improvement, because its order of magnitude is similar to including or not including $TOPO$. We find a similar pattern of rising R^2s in Panels B and C. Notice, for example, the R^2 changes from 11% to 17% when we include the $TOPO$ factor and further changes to 20% when we use our TOP factor.

Overall, our estimation results in this section provide quantitative support for the view that takeover exposure carries indeed a positive and significant premium, further underscoring the pricing ability of the takeover factor. Notably, our augmented takeover factor is associated with a higher premium, implying that the augmented logit model (Model 2) that reflects transparency better captures firms' potential takeover vulnerability.

5 Conclusion

This paper examines whether a firm's transparency influences its takeover probability and links takeover probabilities to stock returns. First, we augment a baseline logit model with transparency and find that they improve the predictive power of a firm's takeover likelihood. Logit estimation coefficients on transparency have the expected sign and are statistically significant. The augmented model not only produces results consistent with prior research, but also increases the Pseudo-R^2 of the logit regression by 20%. Thus, our model fits over 25 years of takeover data significantly better. These findings are robust to using alternative transparency measures (i.e., forecast error and forecast dispersion based on analysts earnings forecasts).

Second, we examine whether the improvement in measuring takeover likelihood affects the relation between takeover likelihood and stock returns. Interestingly, the long-short portfolio formed based on the takeover probability estimated with the augmented model generates higher mean returns and abnormal returns than the long-short portfolio formed with the estimation results of the baseline model. That is, the relation between takeover likelihood and stock returns are actually stronger when takeover likelihood is measured more accurately.

Moreover, our augmented takeover factor (i.e., returns of a long-short portfolio that buys stocks in the top takeover likelihood quintile and sells stocks in the bottom takeover likelihood quintile) performs better than the baseline takeover factor in terms of pricing the cross-section of stock returns. Specifically, the augmented takeover factor reduces abnormal returns to the 25 size and book-to-market portfolios to a lower level than the baseline takeover factor. More important, we find that the premium associated with the augmented takeover factor is higher than that for the baseline factor.

Overall, our results reveal that transparency is crucial for external governance mechanisms, such as takeovers. Future researchers could consider transparency's relation to internal governance mechanisms, such as activist investors or institutional ownership. A few questions that could emerge from such research are whether more transparent firms are more likely to have institutional shareholders (e.g., pension funds), and whether they are more likely to have activist campaigns.

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Appendix

This appendix contains two tables: Table A1 and Table A2. Table A1 reports the intercept α from the time-series regressions of monthly size and book-to-market portfolio returns (value-weighted) on risk factors using different asset-pricing models. Table A2 reports the intercept α from the time-series regressions of monthly size and book-to-market portfolio returns (value-weighted) on risk factors using different asset-pricing models.

Table A1. Pricing the 25 size and book-to-market portfolios (value-weighted)

This table reports the intercept α from the time-series regressions of monthly size and book-to-market portfolio returns (value-weighted) on risk factors using different asset-pricing models. Panel A presents the mean excess return of each portfolio. Panel B presents the α_s for the market model. Panel C reports intercept α_s for a model with the market factor and the augmented takeover factor (TOP). Panel D and Panel E report the α_s for the four-factor model and the augmented five-factor model, respectively. The right part of each panel reports the t-statistics of the estimates. 25 size and book-to-market portfolio returns, Fama-French risk factors, and risk-free rates are obtained from Kenneth-French's website. The momentum factor is constructed according to the procedure in Carhart (1997). The sample period is from 1991 to 2016.

	Book-to-market ratio									
Size	Low	2	3	4	High	Low	2	3	4	High
Panel A : $R_t - R_f$										
	α					t-stat				
Small	0.30	1.01	0.94	1.22	1.28	0.65	2.57	2.96	3.99	4.03
2	0.67	0.92	1.00	1.01	1.06	1.69	2.91	3.50	3.55	3.10
3	0.66	0.97	0.94	1.03	1.20	1.80	3.32	3.49	3.76	3.83
4	0.85	0.89	0.86	1.01	0.86	2.56	3.35	3.14	3.88	2.67
Big	0.67	0.75	0.78	0.52	0.85	2.73	3.24	3.31	1.88	2.51
Panel B : $R_t - R_f = \alpha + \gamma RMRF_t + \epsilon_t$										
	α					t-stat				
Small	-0.67	0.18	0.23	0.57	0.59	2.20	0.68	1.14	2.75	2.83
2	-0.26	0.16	0.33	0.34	0.28	1.15	0.93	2.01	2.08	1.34
3	-0.22	0.23	0.27	0.38	0.49	1.13	1.68	2.02	2.46	2.54
4	0.00	0.21	0.18	0.37	0.11	0.02	1.76	1.32	2.74	0.58
Big	0.01	0.14	0.21	-0.11	0.10	0.14	1.54	1.66	0.66	0.46
Panel C : $R_t - R_f = \alpha + \beta_1 RMRF_t + \gamma TOP_t + \epsilon_t$										
	α					t-stat				
Small	-1.20	-0.45	-0.42	-0.11	-0.23	3.85	1.68	2.32	0.61	1.37
2	-0.60	-0.20	-0.07	-0.08	-0.37	2.53	1.16	0.42	0.51	1.91
3	-0.36	0.00	0.03	0.02	0.13	1.74	0.03	0.19	0.16	0.66
4	-0.02	0.07	-0.06	0.17	-0.21	0.12	0.54	0.42	1.18	1.10
Big	0.20	0.17	0.17	-0.29	-0.20	2.33	1.68	1.21	1.64	0.88
Panel D :$R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \epsilon_t$										
	α					t-stat				
Small	-0.60	0.05	0.06	0.27	0.27	3.82	0.44	0.78	3.05	3.06
2	-0.17	0.03	0.09	0.03	-0.12	1.82	0.42	1.06	0.39	1.49
3	-0.09	0.10	0.07	0.10	0.16	1.01	0.98	0.75	0.96	1.33
4	0.10	0.09	0.00	0.16	-0.16	1.04	0.90	0.01	1.49	1.21
Big	0.15	0.09	0.10	-0.31	-0.13	2.74	1.15	0.99	3.04	0.84
Panel E: $R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \gamma TOP_t + \epsilon_t$										
	α					t-stat				
Small	-0.83	-0.12	-0.10	0.11	-0.01	5.14	0.96	1.27	1.20	0.09
2	-0.15	0.15	0.23	0.15	-0.09	1.52	1.76	2.65	1.95	0.99
3	0.00	0.23	0.23	0.18	0.34	0.05	2.15	2.31	1.64	2.73
4	0.16	0.19	0.03	0.24	-0.09	1.67	1.77	0.25	2.14	0.67
Big	0.11	0.11	0.10	-0.27	-0.26	1.83	1.27	1.00	2.56	1.55

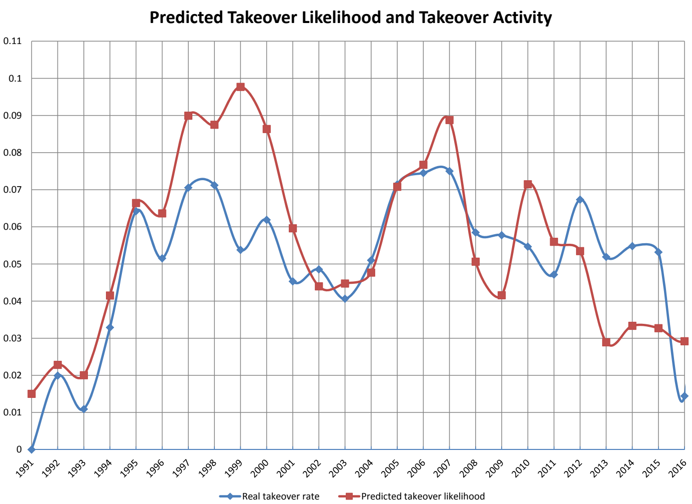
Table A2. Pricing the 25 size and book-to-market portfolios (value-weighted): TOP VS. $TOPO$

This table reports the intercept α from the time-series regressions of monthly size and book-to-market portfolio returns (value-weighted) on risk factors using different asset-pricing models. Panel A presents the mean excess return of each portfolio. Panel B presents the α_s for the Carhart (1997) four-factor model. Panel C reports intercept α_s for the augmented five-factor model with the augmented takeover factor TOP as the fifth pricing factor, and Panel D reports intercept α_s for the augmented five-factor model with the baseline takeover factor as the fifth pricing factor (The baseline takeover factor $TOPO$ is constructed using the baseline logit model.) The right part of each panel reports the t-statistics of the estimates. 25 size and book-to-market portfolio returns, Fama-French risk factors, and risk-free rates are obtained from Kenneth-French's website. The momentum factor is constructed according to the procedure in Carhart (1997). The sample period is from 1991 to 2016.

	Book-to-market ratio									
Size	Low	2	3	4	High	Low	2	3	4	High
	Panel A : $R_t - R_f$									
	α					t-stat				
Small	0.30	1.01	0.94	1.22	1.28	0.65	2.57	2.96	3.99	4.03
2	0.67	0.92	1.00	1.01	1.06	1.69	2.91	3.50	3.55	3.10
3	0.66	0.97	0.94	1.03	1.20	1.80	3.32	3.49	3.76	3.83
4	0.85	0.89	0.86	1.01	0.86	2.56	3.35	3.14	3.88	2.67
Big	0.67	0.75	0.78	0.52	0.85	2.73	3.24	3.31	1.88	2.51
	Panel D :$R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \epsilon_t$									
	α					t-stat				
Small	-0.60	0.05	0.06	0.27	0.27	3.82	0.44	0.78	3.05	3.06
2	-0.17	0.03	0.09	0.03	-0.12	1.82	0.42	1.06	0.39	1.49
3	-0.09	0.10	0.07	0.10	0.16	1.01	0.98	0.75	0.96	1.33
4	0.10	0.09	0.00	0.16	-0.16	1.04	0.90	0.01	1.49	1.21
Big	0.15	0.09	0.10	-0.31	-0.13	2.74	1.15	0.99	3.04	0.84
	Panel E: $R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \gamma TOP_t + \epsilon_t$									
	α					t-stat				
Small	-0.83	-0.12	-0.10	0.11	-0.01	5.14	0.96	1.27	1.20	0.09
2	-0.15	0.15	0.23	0.15	-0.09	1.52	1.76	2.65	1.95	0.99
3	0.00	0.23	0.23	0.18	0.34	0.05	2.15	2.31	1.64	2.73
4	0.16	0.19	0.03	0.24	-0.09	1.67	1.77	0.25	2.14	0.67
Big	0.11	0.11	0.10	-0.27	-0.26	1.83	1.27	1.00	2.56	1.55
	Panel D: $R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \gamma TOPO_t + \epsilon_t$									
	α					t-stat				
Small	-0.65	-0.05	-0.07	0.13	0.08	3.90	0.36	0.88	1.43	1.20
2	-0.13	0.13	0.19	0.13	-0.10	1.38	1.52	2.20	1.66	1.18
3	-0.02	0.19	0.18	0.14	0.34	0.19	1.76	1.72	1.25	2.66
4	0.17	0.17	0.00	0.21	-0.09	1.76	1.55	0.00	1.90	0.63
Big	0.11	0.10	0.09	-0.31	-0.19	1.82	1.16	0.91	2.90	1.17

Figure 1. Predicted takeover likelihood and real takeover activity

This figure plots the time series of the average predicted takeover likelihood and the real takeover rates for the top decile group over the period of 1991 to 2016. Predicted takeover likelihood is computed using estimation coefficients in Table 2 and Equation (2). Each year, firms are sorted into deciles based on the predicted takeover probability. We then calculate the average predicted takeover probability for each decile as the mean value of the takeover probability of firms within the same decile. We compute the realized takeover activity as the takeover event rate within each decile. The time series of the average predicted takeover likelihood and the real takeover rates for decile 10 (with highest predicted takeover likelihood) are plotted in the figure.



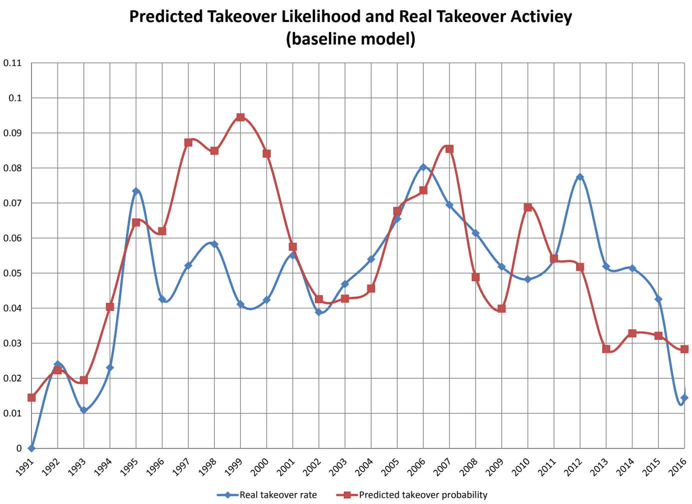


Figure 2. Cumulative return of the long-short portfolio

This figure plots the time series of the cumulative monthly return for the long-short portfolio formed based on the predicted takeover probability over the period of 1991 to 2016. LS1090 refers to the portfolio that buys stocks in the top 10% takeover likelihood group and sells stocks in the bottom 10% takeover likelihood group. Similarly, LS2080 refers to the long-short portfolio sorted in quintiles. M1 refers to the portfolio sorted based on the takeover likelihood using the results from Model 1 and M2 refers to the portfolio sorted based on the takeover likelihood using the estimation results from Model 2.

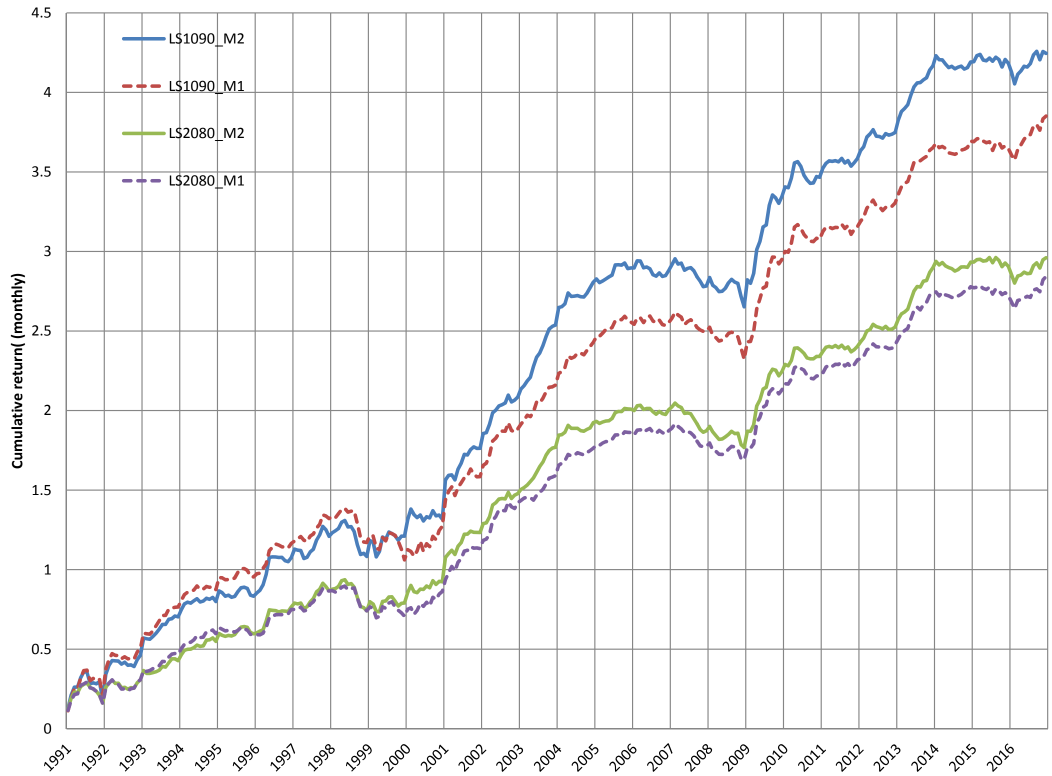


Table 1. Summary statistics

This table presents summary statistics of the independent variables used in the logit estimation model. Q is the ratio of the market value of assets to the book value of assets. PPE is property, plant, and equipment scaled by assets. $Cash$ is the ratio of cash and short-term investments to assets. $Size$ is the natural logarithm of firm market capitalization. $Leverage$ is the book debt scaled by assets. ROA is the return on assets. $Industry$ is the dummy variable which equals one if in the previous year there was at least one takeover event in the firm's industry, which is defined based on Fama-French 48 industry classifications. $Block$ is also a dummy variable that equals 1 if there is at least one institutional owner whose ownership stake in a firm's outstanding shares exceeds 5%, and zero otherwise. $Opacity$ is measured by accrual quality constructed according to McNichols (2002). The data section provides more details about the construction procedure of these variables. Panel A uses all completed takeovers, and Panel B uses 100% completed takeovers. The sample period is from 1991 to 2016. t-stat refers to the t-statistic of the difference of the mean between target and non-target groups.

Variable	Non-Targets Mean	Non-Targets Median	Non-Targets Std. Dev.	Targets Mean	Targets Median	Targets Std. Dev.	t-stat
Panel A: Using all completed takeovers							
Q	2.560	1.455	4.638	1.938	1.366	2.772	5.14
PPE	0.551	0.427	1.332	0.493	0.351	0.825	4.89
$Cash$	0.189	0.095	0.224	0.198	0.106	0.225	2.82
$Size$	5.498	5.399	2.293	5.228	5.139	1.874	10.26
$Leverage$	0.180	0.114	0.276	0.195	0.1212	0.239	4.54
ROA	-0.064	0.027	1.548	-0.059	0.023	0.368	0.76
$Industry$	0.885	1.000	0.319	0.940	1.000	0.238	16.24
$Block$	0.639	1.000	0.480	0.757	1.000	0.429	19.72
$Opacity$	0.029	0.016	0.209	0.023	0.018	0.019	12.01
Obs. of Non-Targets: 76,647							
Obs. of Targets: 3,166							
Panel B: Using 100% completed takeovers							
Q	2.558	1.455	4.548	1.920	1.362	2.805	5.24
PPE	0.552	0.427	1.336	0.481	0.350	0.465	9.08
$Cash$	0.189	0.095	0.224	0.199	0.106	0.227	3.07
$Size$	5.499	5.400	2.294	5.163	5.085	1.788	12.37
$Leverage$	0.180	0.114	0.276	0.188	0.103	0.232	2.23
ROA	-0.064	0.027	1.545	-0.055	0.024	0.368	1.32
$Industry$	0.863	1.000	0.344	0.933	1.000	0.250	18.37
$Block$	0.639	1.000	0.480	0.756	1.000	0.429	18.11
$Opacity$	0.029	0.016	0.209	0.024	0.018	0.019	10.04
Obs. of Non-Targets: 77,185							
Obs. of Targets: 2,628							

Table 2. Logit estimation of takeover likelihood

This table presents the results of the logit regression. The dependent variable is a dummy variable that equals one if the firm is a takeover target in that year. The vector of independent variables includes Q, PPE, $Cash$, $Size$, $Leverage$, ROA, $Industry$, $Block$, and $Opacity$. Q is the ratio of the market value of assets to the book value of assets. PPE is property, plant, and equipment scaled by assets. $Cash$ is the ratio of cash and short-term investments to assets. $Size$ is the natural logarithm of firm market capitalization. $Leverage$ is the book debt scaled by assets. ROA is the return on assets. $Industry$ is the dummy variable that equals one if in the previous year there was at least one takeover event in a firm's industry, which is defined based on Fama-French 48 industry classifications. $Block$ is also a dummy variable that equals 1 if there is at least one institutional owner whose ownership stake in a firm's outstanding shares exceeds 5%, and zero otherwise. $Opacity$ is measured by accrual quality constructed according to McNichols (2002). All explanatory variables are measured one year prior to the event year. Results for both all completed takeovers and 100% completed takeovers are reported. Model 1 and Model 2 refer to the baseline model and our augmented model, respectively. The sample period is from 1991 to 2016. t-statistics are reported in parentheses under the estimation coefficient. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Model 1		Model 2	
Indep. variable	All completed deals	100% completed deals	All completed deals	100% completed deals
Q	-0.065***	-0.070***	-0.049***	-0.053***
	(4.46)	(4.21)	(3.32)	(3.21)
PPE	0.045*	0.008	0.038	-0.007
	(1.83)	(0.21)	(1.45)	(0.18)
$Cash$	0.317***	0.176	0.356***	0.206
	(2.86)	(1.43)	(3.18)	(1.65)
$Size$	-0.101***	-0.107***	-0.122***	-0.126***
	(11.02)	(10.54)	(12.65)	(11.94)
$Leverage$	0.298***	0.250***	0.297***	0.251***
	(4.57)	(2.83)	(4.60)	(2.89)
ROA	0.209***	0.196***	0.202***	0.189***
	(4.08)	(3.61)	(3.389)	(3.40)
$Industry$	0.567***	0.563***	0.592***	0.586***
	(6.77)	(6.59)	(7.06)	(6.87)
$Block$	0.664***	0.693***	0.653***	0.681***
	(14.02)	(13.49)	(13.79)	(13.27)
$Opacity$			-5.431***	-5.224***
			(6.56)	(5.80)
Observations	79,813	79,813	79,813	79,813
Targets	3,166	2,628	3,166	2,628
Pseudo-R^2	3.53%	3.78%	4.38%	4.60%

Table 3. Logit estimation of takeover likelihood: alternative transparency measures

This table presents the results of the logit regression using alternative transparency measures, which are constructed from the analyst earnings forecasts. The dependent variable is a dummy variable that equals one if the firm is a takeover target in that year. The vector of independent variables includes Q, PPE, $Cash$, $Size$, $Leverage$, ROA, $Industry$, $Block$, and $Opacity$. Q is the ratio of the market value of assets to the book value of assets. PPE is property, plant, and equipment scaled by assets. $Cash$ is the ratio of cash and short-term investments to assets. $Size$ is the natural logarithm of firm market capitalization. $Leverage$ is the book debt scaled by assets. ROA is the return on assets. $Industry$ is the dummy variable that equals one if in the previous year there was at least one takeover event in a firm's industry, which is defined based on Fama-French 48 industry classifications. $Block$ is also a dummy variable that equals 1 if there is at least one institutional owner whose ownership stake in a firm's outstanding shares exceeds 5%, and zero otherwise. $Opacity$ is measured by analyst variables: forecast error and forecast dispersion. Forecast error is defined as the absolute value of the difference between the actual annual earnings per share (EPS) and the mean of analyst forecasts. Forecast dispersion is defined as the forecast standard deviation across all analysts following the same firm in the same year. All explanatory variables are measured one year prior to the event year. Results for both all completed takeovers and 100% completed takeovers are reported. The sample period is from 1991 to 2016. t-statistics are reported in parentheses under the estimation coefficient. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	Forecast Error		Forecast Dispersion	
Indep. variable	All completed deals	100% completed deals	All completed deals	100% completed deals
Q	–0.031**	-0.031**	-0.028**	-0.029**
	(2.54)	(2.32)	(2.36)	(2.22)
PPE	–0.063	–0.052	–0.065	–0.042
	(1.05)	(0.78)	(1.05)	(0.63)
$Cash$	0.079	0.040	0.087	0.073
	(0.71)	(0.34)	(0.78)	(0.60)
$Size$	–0.215***	–0.247***	–0.215***	–0.247***
	(16.84)	(17.51)	(16.99)	(17.68)
$Leverage$	0.481***	0.398***	0.498***	0.428***
	(5.85)	(4.32)	(6.08)	(4.67)
ROA	–0.167***	–0.166***	–0.161***	–0.177***
	(2.92)	(2.69)	(2.95)	(2.94)
$Industry$	0.381***	0.463***	0.411***	0.476***
	(4.21)	(4.96)	(4.51)	(5.10)
$Block$	0.309***	0.285***	0.304***	0.279***
	(5.92)	(5.20)	(5.85)	(5.09)
$Opacity$	–0.721***	–1.518***	–0.914***	–2.449***
	(4.03)	(5.46)	(4.29)	(6.14)
Observations	66,908	66,778	66,828	66,697
Targets	3,166	2,628	3,166	2,628
Pseudo-R^2	4.45%	5.97%	4.47%	5.94%

Table 4. Predicted takeover probability and real takeover activity

This table reports the average predicted takeover likelihood estimated from the logit model and the real takeover rate. For each year, the sample used in the logit estimation in Table 2 is sorted into deciles or 20 equal-size portfolios based on the predicted takeover likelihood. Predicted takeover likelihood is computed using estimation coefficients in Table 2 and Equation (2). Then, we calculate the average predicted takeover probability for each portfolio as the mean value of the takeover probability of firms within the same group. The realized takeover rate is computed as the takeover event rate within each group for each year. The average value of predicted takeover probability and the real takeover rate over the sample period of 1991 to 2016 are reported in the table. Panel A and Panel B report the results for decile portfolios and 20 equal-size portfolios, respectively. The results using Model 1 and Model 2 are shown in the left and right part of the table, respectively. Model 1 refers to the baseline logit model, and Model 2 refers to our augmented model with transparency as the additional variable.

	Model 1		Model 2	
	Predicted Takeover Likelihood	Real Takeover Rate	Predicted Takeover Likelihood	Real Takeover Rate
Panel A: Decile Portfolios				
Low	0.0122	0.0104	0.0115	0.0095
2	0.0180	0.0205	0.0175	0.0176
3	0.0227	0.0230	0.0221	0.0234
4	0.0263	0.0258	0.0260	0.0277
5	0.0295	0.0245	0.0293	0.0290
6	0.0326	0.0288	0.0325	0.0292
7	0.0360	0.0352	0.0359	0.0332
8	0.0398	0.0420	0.0398	0.0377
9	0.0442	0.0537	0.0447	0.0537
High	0.0523	0.0495	0.0541	0.0524
Panel B: 20 Equal-size Portfolios				
Low	0.0102	0.0063	0.0093	0.0056
2	0.0142	0.0145	0.0137	0.0133
3	0.0168	0.0201	0.0163	0.0180
4	0.0193	0.0209	0.0187	0.0172
5	0.0216	0.0196	0.0210	0.0230
6	0.0237	0.0264	0.0231	0.0238
7	0.0255	0.0285	0.0251	0.0237
8	0.0271	0.0233	0.0268	0.0316
9	0.0287	0.0247	0.0285	0.0300
10	0.0303	0.0244	0.0302	0.0280
11	0.0318	0.0297	0.0318	0.0273
12	0.0334	0.0280	0.0333	0.0311
13	0.0351	0.0302	0.0350	0.0324
14	0.0369	0.0402	0.0368	0.0340
15	0.0388	0.0420	0.0388	0.0388
16	0.0408	0.0420	0.0409	0.0367
17	0.0429	0.0556	0.0433	0.0535
18	0.0454	0.0517	0.0462	0.0540
19	0.0488	0.0531	0.0499	0.0525
High	0.0558	0.0459	0.0582	0.0523

Table 5. Takeover likelihood and equity return relation

This table reports the monthly returns and abnormal returns to the quintile portfolios formed based on a firm's takeover likelihood, which is constructed using the logit estimation coefficients in Table 2. Results for all completed deals sample and 100% completed deals sample are presented in Panel A and Panel B, respectively. In each panel, the equal-weighted mean return to the quintile portfolio, both equal-weighted and value-weighted return spreads and abnormal returns to the quintile or decile hedge portfolio that buys firms with the highest takeover probability and sells firms with the lowest takeover probability, and the returns and abnormal returns to the long-short portfolio when the takeover probability is constructed using the logit estimation of the baseline model are also shown at the bottom of each panel for comparison's sake. To correct the in-sample "look-ahead" bias, we estimate the logit model using 10-year rolling windows and report the portfolio return results in the right part of the table. The sample period is from 1991 to 2016. *t*-statistics are reported after the estimation coefficient.

	Whole sample logit estimation				Rolling windows logit estimation			
Takeover prob	Mean	*t*-stat	Alpha	*t*-stat	Mean	*t*-stat	Alpha	*t*-stat
Panel A: All completed deals sample								
Low	0.91%	3.34	-0.03%	-0.33	0.73%	1.98	0.05%	0.38
2	1.28%	4.40	0.39%	3.29	1.08%	2.92	0.42%	3.06
3	1.47%	5.18	0.44%	5.13	1.23%	3.30	0.46%	4.33
4	1.34%	4.22	0.23%	2.84	1.22%	2.86	0.29%	2.67
High	1.81%	5.49	0.86%	5.57	1.71%	5.35	0.75%	5.32
H-L(EW)	0.90%	5.51	0.86%	5.74	0.98%	4.91	0.71%	4.90
H-L(VW)	0.79%	3.35	0.50%	3.96	0.96%	3.22	0.53%	3.10
H-L(EW, decile)	1.30%	5.68	1.34%	6.69	1.39%	4.96	1.29%	5.21
H-L(VW, decile)	1.13%	3.79	0.83%	4.42	1.34%	3.53	0.85%	3.58
H-L(EW)	0.86%	5.73	0.83%	6.62	0.96%	5.31	0.82%	5.42
H-L(VW)	0.76%	3.33	0.45%	3.97	0.95%	3.28	0.46%	3.14
H-L(EW, decile)	1.18%	5.81	1.22%	6.96	1.28%	5.28	1.18%	5.59
H-L(VW, decile)	0.91%	3.54	0.63%	4.07	1.12%	3.44	0.65%	3.26
Panel B: 100% completed deals sample								
Low	0.90%	3.37	-0.04%	0.37	0.72%	1.99	0.04%	0.31
2	1.25%	4.18	0.33%	2.75	1.04%	2.69	0.34%	2.39
3	1.50%	5.36	0.50%	5.48	1.27%	3.47	0.53%	4.66
4	1.35%	4.29	0.25%	3.22	1.21%	2.87	0.30%	2.83
High	1.79%	5.43	0.82%	5.39	1.71%	5.36	0.74%	5.29
H-L(EW)	0.88%	5.46	0.86%	5.55	1.00%	5.01	0.91%	4.85
H-L(VW)	0.85%	3.55	0.57%	4.28	0.96%	3.60	0.68%	3.71
H-L(EW, decile)	1.33%	5.85	1.38%	6.83	1.44%	5.17	1.36%	5.39
H-L(VW, decile)	1.25%	4.29	0.98%	5.19	1.36%	4.05	0.76%	4.32
H-L(EW)	0.85%	5.68	0.82%	6.56	0.98%	5.42	0.84%	5.54
H-L(VW)	0.76%	3.34	0.45%	4.00	0.89%	3.42	0.50%	3.39
H-L(EW, decile)	1.26%	6.16	1.30%	7.20	1.39%	5.66	1.14%	5.95
H-L(VW, decile)	1.10%	4.06	0.83%	4.93	1.32%	3.88	0.62%	3.97

Table 6. Summary statistics of factors

This table lists summary statistics of the takeover factor, the Fama-French three factors, and the momentum factor constructed according to Carhart (1997). The five factors are denoted by TOP (takeover factor), MKT (market factor), SML (size factor), HML (value factor), and UMD (momentum factor), respectively. The takeover factor is constructed as the monthly equal-weighted portfolio return to the hedge portfolio that is long in firms in the top takeover likelihood quintile and short in firms from the bottom takeover likelihood quintile. Panel A lists some basic statistics of the five factors. $SKEW$ and $KURT$ refer to skewness and kurtosis, respectively. Panel B lists the correlation matrix of these factors. The sample period is from 1991 to 2016.

Panel A: Basic descriptive statistics					
	Mean	t–stat	STD	SKEW	KURT
MKT	0.72	3.11	4.17	-0.71	1.53
SMB	0.23	1.32	3.09	0.48	5.35
HML	0.25	1.49	3.03	0.16	2.56
UMD	0.40	1.18	6.03	-1.41	8.26
TOP	0.76	3.33	4.08	0.44	1.92
Panel B: Correlation matrix of factors					
	MKT	SMB	HML	UMD	TOP
MKT	1.00				
SMB	0.20	1.00			
HML	-0.16	-0.11	1.00		
UMD	-0.32	-0.03	-0.10	1.00	
TOP	0.19	0.33	0.15	-0.20	1.00

Table 7. Pricing the 25 size and book-to-market portfolios (equal-weighted)

This table reports the intercept α from the time-series regressions of monthly size and book-to-market portfolio returns (equal-weighted) on risk factors using different asset-pricing models. Panel A presents the mean excess return of each portfolio. Panel B presents the α_s for the market model. Panel C reports intercept α_s for a model with the market factor and the augmented takeover factor (TOP). Panel D and Panel E report the α_s for the four-factor model and the augmented five-factor model, respectively. The right part of each panel reports the t-statistics of the estimates. 25 size and book-to-market portfolio returns, Fama-French risk factors, and risk-free rates are obtained from Kenneth-French's website. The momentum factor is constructed according to the procedure in Carhart (1997). The sample period is from 1991 to 2016.

	Book-to-market ratio									
Size	Low	2	3	4	High	Low	2	3	4	High
Panel $A: R_t - R_f$										
	α					t-stat				
Small	0.45	1.00	1.11	1.26	1.56	0.91	2.54	3.34	4.28	4.78
2	0.65	0.97	1.10	1.04	1.08	1.53	2.87	3.64	3.45	2.96
3	0.70	1.00	1.00	1.09	1.26	1.77	3.22	3.45	3.74	3.62
4	0.83	0.89	0.89	1.03	0.88	2.40	3.16	3.07	3.69	2.47
Big	0.69	0.78	0.89	0.76	0.98	2.45	3.12	3.59	2.76	2.90
Panel $B: R_t - R_f = \alpha + \gamma RMRF_t + \epsilon_t$										
	α					t-stat				
Small	-0.51	0.18	0.39	0.64	0.91	1.41	0.65	1.78	3.17	3.83
2	-0.34	0.15	0.38	0.33	0.25	1.36	0.84	2.26	1.92	1.11
3	-0.26	0.22	0.28	0.40	0.47	1.20	1.46	1.94	2.42	2.19
4	-0.06	0.18	0.18	0.35	0.06	0.41	1.34	1.20	2.38	0.27
Big	-0.07	0.13	0.30	0.13	0.23	0.83	1.24	2.16	0.79	1.07
Panel $C: R_t - R_f = \alpha + \beta_1 RMRF_t + \gamma TOP_t + \epsilon_t$										
	α					t-stat				
Small	-1.29	-0.66	-0.41	-0.20	-0.12	3.61	2.63	2.19	1.29	0.68
2	-0.79	-0.29	-0.10	-0.19	-0.53	3.09	1.67	0.63	1.16	2.71
3	-0.49	-0.11	-0.04	-0.04	-0.05	2.22	0.71	0.28	0.26	0.25
4	-0.14	-0.02	-0.15	0.10	-0.40	0.90	0.12	0.97	0.63	1.93
Big	-0.03	0.05	0.17	-0.10	-0.16	0.31	0.47	1.17	0.60	0.73
Panel $D: R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \epsilon_t$										
	α					t-stat				
Small	-0.23	0.27	0.39	0.51	0.78	0.92	1.55	2.95	4.25	4.76
2	-0.08	0.14	0.22	0.07	0.09	0.65	1.55	2.54	0.85	0.98
3	0.05	0.16	0.15	0.15	0.20	0.38	1.45	1.50	1.49	1.56
4	0.17	0.10	0.05	0.17	0.13	1.66	0.89	0.44	1.53	0.94
Big	0.14	0.09	0.17	0.05	0.06	2.10	1.00	1.65	0.46	0.39
Panel E: $R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \gamma TOP_t + \epsilon_t$										
	α					t-stat				
Small	-0.88	-0.29	-0.07	0.04	0.09	3.66	1.83	0.59	0.37	0.69
2	-0.18	0.18	0.31	0.14	-0.15	1.44	1.85	3.38	1.73	1.51
3	0.04	0.25	0.30	0.20	0.31	0.29	2.22	2.92	1.84	2.21
4	0.19	0.17	0.04	0.22	-0.16	1.74	1.43	0.30	1.82	1.08
Big	0.11	0.13	0.19	-0.03	-0.03	1.51	1.32	1.79	0.24	0.20

Table 8. Pricing the 25 size and book-to-market portfolios (equal-weighted): TOP VS. $TOPO$

This table reports the intercept α from the time-series regressions of monthly size and book-to-market portfolio returns (equal-weighted) on risk factors using different asset-pricing models. Panel A presents the mean excess return of each portfolio. Panel B presents the α_s for the Carhart (1997) four-factor model. Panel C reports intercept α_s for the augmented five-factor model with the augmented takeover factor TOP as the fifth pricing factor, and Panel D reports intercept α_s for the augmented five-factor model with the baseline takeover factor as the fifth pricing factor (The baseline takeover factor $TOPO$ is constructed using the baseline logit model.) The right part of each panel reports the t-statistics of the estimates. 25 size and book-to-market portfolio returns, Fama-French risk factors, and risk-free rates are obtained from Kenneth-French's website. The momentum factor is constructed according to the procedure in Carhart (1997). The sample period is from 1991 to 2016.

	Book-to-market ratio									
Size	Low	2	3	4	High	Low	2	3	4	High
	Panel A : $R_t - R_f$									
	α					t-stat				
Small	0.45	1.00	1.11	1.26	1.56	0.91	2.54	3.34	4.28	4.78
2	0.65	0.97	1.10	1.04	1.08	1.53	2.87	3.64	3.45	2.96
3	0.70	1.00	1.00	1.09	1.26	1.77	3.22	3.45	3.74	3.62
4	0.83	0.89	0.89	1.03	0.88	2.40	3.16	3.07	3.69	2.47
Big	0.69	0.78	0.89	0.76	0.98	2.45	3.12	3.59	2.76	2.90
	Panel B :$R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \epsilon_t$									
	α					t-stat				
Small	-0.23	0.27	0.39	0.51	0.78	0.92	1.55	2.95	4.25	4.76
2	-0.08	0.14	0.22	0.07	0.09	0.65	1.55	2.54	0.85	0.98
3	0.05	0.16	0.15	0.15	0.20	0.38	1.45	1.50	1.49	1.56
4	0.17	0.10	0.05	0.17	0.13	1.66	0.89	0.44	1.53	0.94
Big	0.14	0.09	0.17	0.05	0.06	2.10	1.00	1.65	0.46	0.39
	Panel C: $R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \gamma TOP_t + \epsilon_t$									
	α					t-stat				
Small	-0.88	-0.29	-0.07	0.04	0.09	3.66	1.83	0.59	0.37	0.69
2	-0.18	0.18	0.31	0.14	-0.15	1.44	1.85	3.38	1.73	1.51
3	0.04	0.25	0.30	0.20	0.31	0.29	2.22	2.92	1.84	2.21
4	0.19	0.17	0.04	0.22	-0.16	1.74	1.43	0.30	1.82	1.08
Big	0.11	0.13	0.19	-0.03	-0.03	1.51	1.32	1.79	0.24	0.20
	Panel D: $R_t - R_f = \alpha + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_2 UMD_t + \gamma TOPO_t + \epsilon_t$									
	α					t-stat				
Small	-0.54	-0.10	0.06	0.12	0.21	2.10	0.60	0.42	1.09	1.43
2	-0.11	0.18	0.27	0.11	-0.16	0.88	1.85	2.86	1.37	1.68
3	0.06	0.21	0.23	0.15	0.28	0.45	1.80	2.20	1.42	1.99
4	0.21	0.14	0.00	0.20	-0.15	1.93	1.20	0.02	1.64	1.00
Big	0.10	0.10	0.15	-0.08	-0.05	1.38	1.01	1.40	0.71	0.32

Table 9. Premium associated with the takeover exposure

This table reports the coefficients of the regression of mean excess returns of each of the 100 size and book-to-market portfolios on the portfolio betas, which are computed as the coefficients of the regression of the excess return of each of the 100 portfolios on factors. TOP refers to the takeover factor constructed using the augmented logit estimation results, and $TOPO$ refers to the takeover factor constructed using the baseline logit estimation results. 100 size and book-to-market portfolio returns, Fama-French risk factors, and risk-free rates are obtained from Kenneth-French's website. The momentum factor is constructed according to the procedure in Carhart (1997). The sample period is from 1991 to 2016.

Panel A: Pricing with the Carhart (1997) Four-Factor Model						
	FF4	*t*-stat	FF4 + TOPO	*t*-stat	FF4 +TOP	*t*-stat
Intercept	0.16	(6.38)	0.15	(6.85)	0.15	(6.97)
MARKET	-0.06	(2.20)	-0.07	(2.74)	-0.07	(2.85)
SIZE	0.05	(5.29)	0.04	(5.50)	0.04	(5.73)
HML	0.03	(4.01)	0.04	(5.96)	0.04	(5.44)
UMD	0.04	(3.60)	0.04	(2.90)	0.04	(2.88)
TOPO			0.05	(4.78)		
TOP					0.06	(5.51)
R^2	0.38		0.45		0.53	

Panel B: Pricing with the Fama-French Three-Factor Model						
	FF3	*t*-stat	FF3 + TOPO	*t*-stat	FF3 +TOP	*t*-stat
Intercept	0.18	(7.18)	0.17	(7.54)	0.17	(7.55)
MARKET	-0.10	(4.19)	-0.10	(4.52)	-0.10	(4.50)
SIZE	0.03	(4.05)	0.03	(4.60)	0.03	(4.81)
HML	0.03	(5.06)	0.05	(7.21)	0.04	(7.02)
TOPO			0.05	(5.31)		
TOP					0.07	(5.59)
R^2	0.33		0.41		0.49	

Panel C: Pricing with the Capital Asset Pricing Model (CAPM)						
	CAPM	*t*-stat	CAPM + TOPO	*t*-stat	CAPM + TOP	*t*-stat
Intercept	0.20	(7.09)	0.20	(7.12)	0.19	(6.93)
MARKET	-0.10	(3.53)	-0.10	(3.54)	-0.09	(3.32)
TOPO			0.03	(2.67)		
TOP					0.05	(3.55)
R^2	0.11		0.17		0.20	

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