The Art of the (no) Deal

Identifying the Drivers of Canceled M&A Deals

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Globally, almost 54,000 merger and acquisition ("M&A") deals with a total value of $4.1 trillion were announced in 2017[1]. While investors generally expect announced deals to close, not all do. Terminated deals impact capital market participants in various ways. Predicting deals that are likely to be canceled is of interest to both M&A advisers and equity investors. Certain drivers influence whether a deal is likely to be canceled:

- **Size:** The larger the size of the target (acquirer), the more difficult (easier) it is for the acquirer to finance the deal (Figure 2).
- **Deal Proportionality** (deal size to acquirer's market cap): Deals with large proportionality ratios ("mergers of equals"), can be difficult to manage (who leads the combined entity, board membership constitution, etc.), leading to a higher cancelation risk for these type of transactions.
- **Perceived Price Discount:** Shareholders of targets with stock prices well off their 52-week highs often believe their positions are worth more than the offer price, and existing management usually encourage this point of view.
- **CEO Age:** Deals where the acquirer CEO is a young male, have a higher risk of being terminated than deals involving older CEOs, as younger male CEOs can be less diplomatic, more combative and less willing to concede in negotiations.
- **Regulatory Risk:** Deals where both the target and acquirer account for a large share of total industry assets have a higher risk of being terminated (antitrust concerns) than deals where this is not the case.
- **A model comprised of 4 drivers forecasts the rate of M&A cancelations at twice the level (26%) of the M&A universe (13%).**

We also confirm academic findings around excess returns to both targets and acquirers on deal announcement and canceled dates (Table 3 and Table 4). **Targets earn an average excess return of 7.79%[2] (-3.35%) in the three day window surrounding deal announcement (cancelation)**, both statistically significant at the 1% level. The average excess return to acquirers in this same window is not significant.

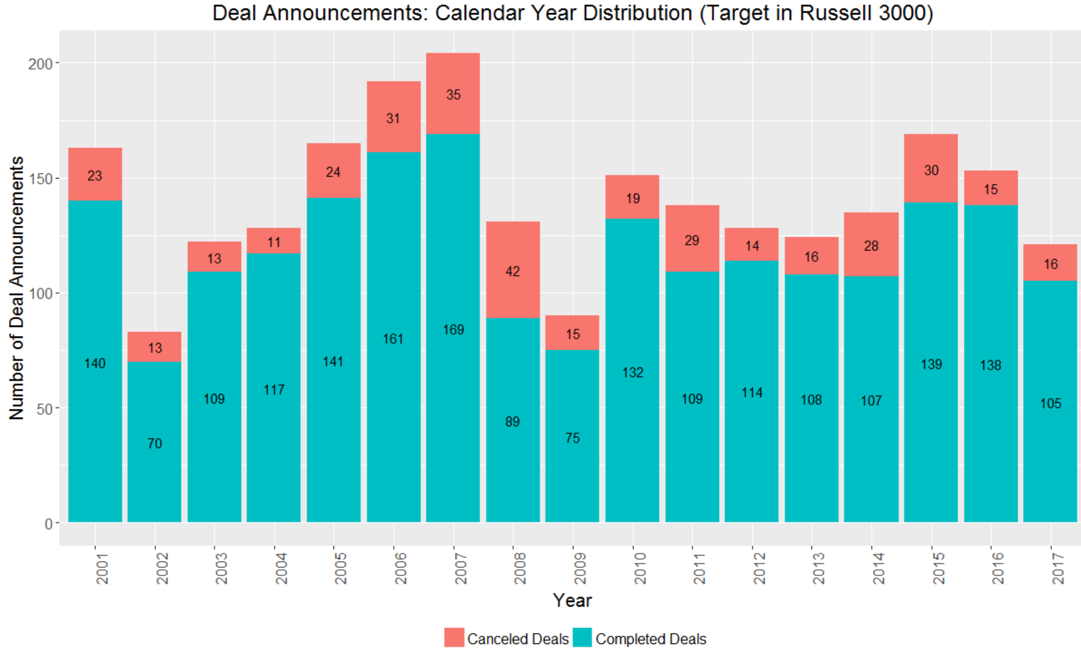
1. Introduction

Academic papers document positive abnormal returns to targets of a deal. Dodd (1980) documented abnormal returns of 4.3% to targets on announcement date. Malmendier et al. (2016) reached a similar conclusion as Dodd, but also reported higher announcement day returns for targets when the acquisition was cash versus stock-based.

However, a certain percentage of announced deals fail to close. Figure 1 shows the breakdown (completed and canceled) of all deals announced between January 2001 and December 2017, for Russell 3000 targets. Total deals peaked in 2007, prior to the beginning of the financial crisis, and bottomed out around recessions (2002, 2009). The highest termination rate was in 2008 (32%).

[1] Source S&P Global Market Intelligence as at 1/3/2018
[2] Excess returns are calculated after controlling for market, value, size and momentum risk factors.

Figure 1: Deal Announcements – Calendar Year Distribution (Target in Russell 3000) January 2001 – December 2017



Source: S&P Global Market Intelligence Quantamental Research. Data as at 01/25/2018

Announced deals fail to close for a variety of reasons:

- Shareholders and/or directors of the target believe the terms of the deal undervalues the firm and push for a higher offer.
- Material changes in company or industry fundamentals can occur subsequent to the deal's announcement, such as occurred during the 2008 financial crisis.
- Anti-trust and national security concerns (cross-border deals / foreign ownership).

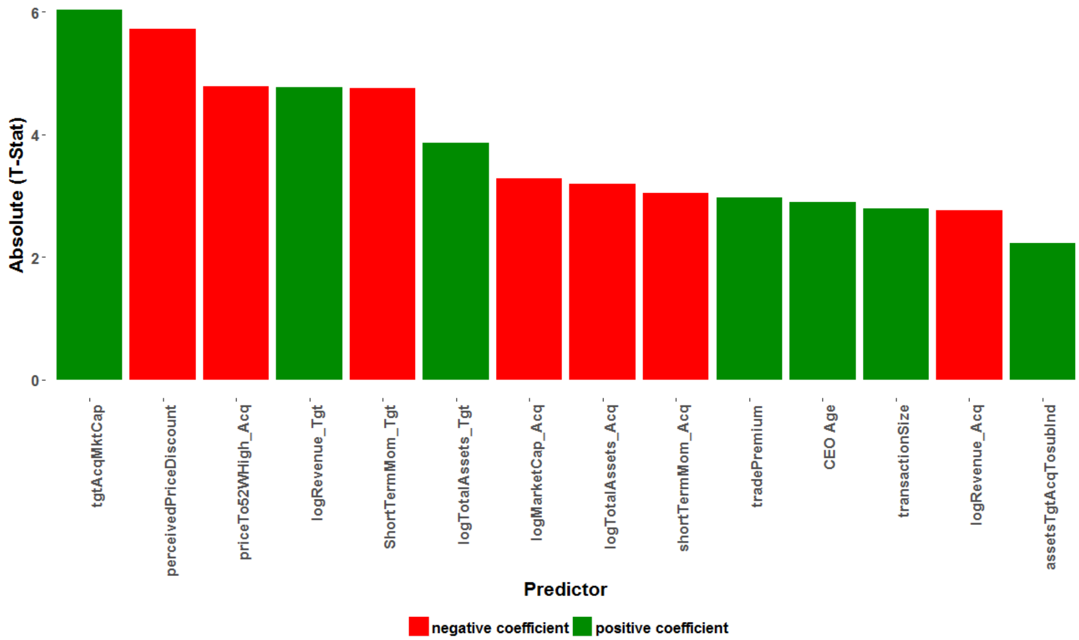
Cole et al. (2006) reported that targets' abnormal returns around deal announcements are not completely reversed at termination, as the announcement of an offer generates new information regarding the perceived value of the target.

Researchers have documented several characteristics that increase the cancelation risk of M&A deals. Branch and Wang (2008) reported a positive relationship between the relative size of the target to the acquirer and deal cancelation risk. Levi et al. (2010) found that cancelation risk was higher when the acquirer's CEO was young and male.

2. Predicting Deal Cancelation Risk

We estimated the probability of a deal being terminated using logistic regression. Our universe consists of 2,300 observations, of which 361 were canceled and the remaining were closed deals. We randomly selected two-thirds of our sample as the in-sample period and the remaining one-third as out-of-sample. Selected predictors with significant t-stats are shown in Figure 2 (See Appendix A for list of factors tested). **Analyses in the following sections were conducted with data as at March 2017**.

Figure 2: Predictors with Significant T-Stats: Target in Russell 3000 (January 2001 – March 2017)



Source: S&P Global Market Intelligence Quantamental Research. Data as at 09/30/2017.
Suffix "tgt" and "acq" indicate target or acquirer characteristics respectively. Green (red) bars indicate that the predictor has a positive (negative) relationship with deal cancelation risk. For example, deals with high "tgtAcqMktCap" values (ratio of the target's market capitalization to that of the acquirer) have a higher probability of being terminated than deals with low tgtAcqMktCap values – a positive relationship

Figure 2 is dominated by size-related/proportionality factors (tgtAcqMktCap, transactionSize, logRevenue_Tgt, logTotAssets_Tgt) as well as factors related to pre-deal price momentum (percievedPriceDiscount, shortTermMom).

Large acquirers are in a better position to close deals due to stronger balance sheets and easier access to financing than smaller companies. However, the size of the target relative to the size of the acquirer is also an important metric, as very large acquisitions are difficult to consummate.

Deals with targets trading well below 52-week highs are at risk of not closing (perceivedPriceDiscount**)**. Shareholders "anchoring" the value of their stock to the high over the past year may believe their stock is being acquired too cheaply and not support the deal.

Regulatory risk is another important consideration. **The larger our metric of regulatory risk** (assetsTgtAcqToSubInd), **the higher the cancelation risk**, as deals that would result in significant industry consolidation are likely to face antitrust scrutiny.

We also found **the age of the acquirer's CEO** to be an important characteristic, as young male CEOs may be more combative and less willing to concede in negotiations, compared to older CEOs[3].

[3] CEO Age is a binary indicator set to 1 for male CEOs (50 years or less).

We tested several fundamental metrics (Appendix A), including earnings yield, book leverage and return on assets as possible drivers of canceled deals, but our results were inconclusive.

Although our data sample is small, three of the four predictors included in the model have coefficients that are significant at the 1% level (Table 1)[4].

Table 1: Predictor Coefficients (in-sample): Target in Russell 3000 (January 2001-March 2017)

Predictor	Coefficient
Perceived Price Discount	-2.07***
Log of Revenue - Target	0.29***
Transaction Size	0.37***
CEO Age	0.45*

*** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. Data as at 09/30/2017.

2.1. Model Performance (Out-of-sample)

We used two methods to measure the performance of the model (out-of-sample data):

1) Binning: We bin all probability values generated by the model and compare the cancelation hit rate[5] of each bin (number of deals that were actually terminated divided by number of deals in the bin) to the cancelation rate of the out-of-sample universe (13%).

The cancelation hit rate of Bin 5 (high risk deals) is 26%, twice the cancelation rate of the universe (Table 2). Deals in Bin 5 are more likely to be terminated than deals in Bins 1 through 4. Also, deals in Bin 1 usually close, with only 2% of these deals canceled.

Table 2: Cancelation Hit-Rates Based on Out-sample Data (Target in Russell 3000 Universe): January 2001 – March 2017

Bin	Hit Rate
Lowest Predicted Risk (1)	2%***
2	9%
3	15%
4	14%
Highest Predicted Risk (5)	26%***
Universe Cancelation Rate	13%

*** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. Data as at 09/30/2017.

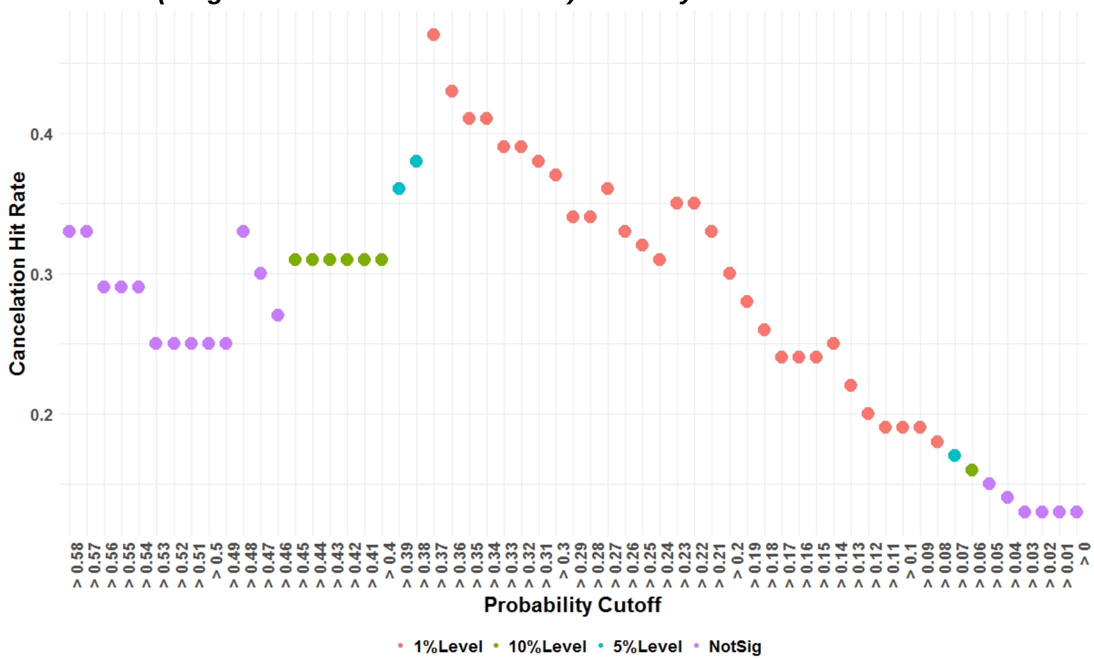
2) Probability cut-off: We calculate the cancelation hit rate for all deals with probability values greater than a given threshold. For example, we classify all deals with probability

[4] Three-fifths of the data was for in-sample and two-fifths for out-sample. This approach yields 826 and 552 observation for the in-sample and out-of-sample respectively.
[5] Cancelation hit rate for a quintile/cohort/universe is the number of deals that were actually canceled in that quintile/cohort divided by the number of deals in that quintile/cohort.

values greater than 0.50 as “canceled” and then determine the cancelation hit rate at this cut-off level. This process can be applied to all probability values between 0 and 1.

The forecasted cancelation hit rate of the model is higher than the universe realized cancelation rate (13%), and the difference is statistically significant at the 1% level, for model probability values between 9% and 39% **(Figure 3).** The difference in hit rate is not significant at model forecasted probability values larger than 45%, as the model generates only a few probability values above this cut-off**.**

Figure 3: Cancelation Hit-Rate Based on Different Cut-off Thresholds (Target in Russell 3000 Universe): January 2001 – March 2017



Source: S&P Global Market Intelligence Quantamental Research. Data as at 09/30/2017
The probability cut-off goes from left to right in deceasing order[6]. For example “>0.58” means that we classify all probability values greater than 0.58 as “canceled”. We then determine the cancelation hit rate at this cut-off level. The color of each dot indicates the significance level of the hit rate, with purple dots (“NotSig”) used for hit rates that are not significant.

2.2. Comparing the 4-factor Model to a Benchmark Model

What if we compared our model to one based on the market’s reaction to the announcement of the deal (a “benchmark” model)?

The benchmark model[7] is calculated by:

a) Taking the difference of the target price 1-day after deal announcement and 1-month before announcement.
b) Calculating the offer spread: offer price minus target price 1-month before announcement.
c) Dividing (a) by (b). The ratio value is proportional to the market’s confidence in the deal closing.

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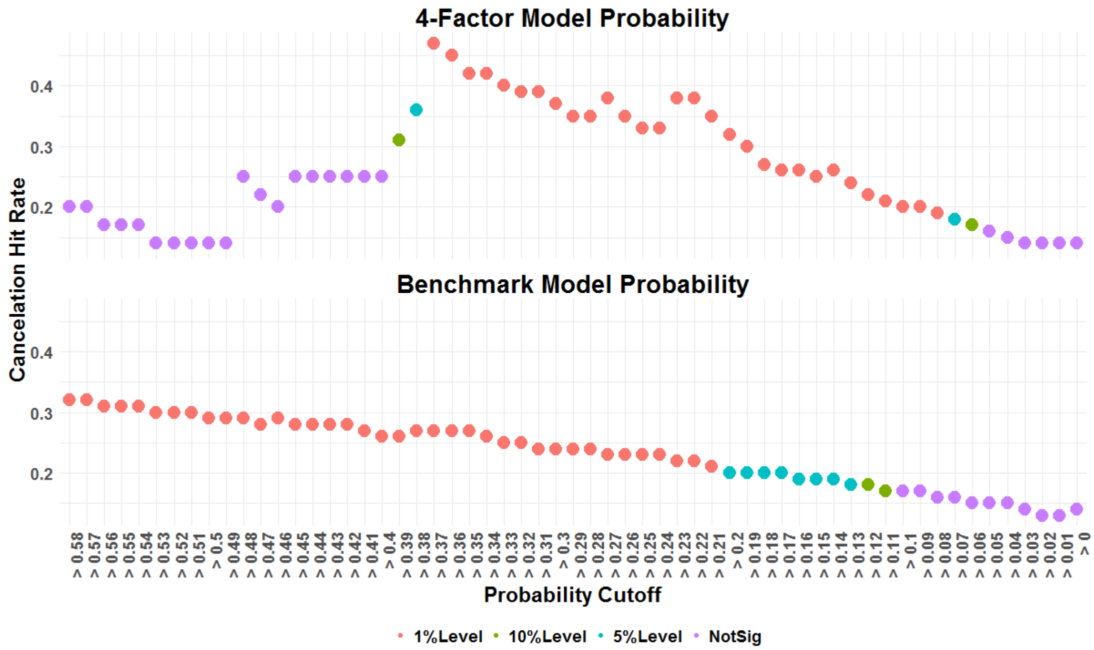
[6] We start at a cut-off point of 0.58 since cut-off values higher than 0.58 did not yield statistically significant hit rates.
[7] See Appendix C for detailed description.

The 4-factor model has higher cancelation hit rates than the benchmark model when both models have hit rates that are significant at the 1% level (p-values are based on baseline rate of 13%, **Figure 4**). In addition, the difference in cancelation hit rates between both models is significant at the 1% level for a subset of probability values (See Appendix B). Readers using a similar type of benchmark model can improve cancelation risk prediction by using a model such as the 4-factor model.

Figure 4: Cancelation Hit-Rate Based on Different Cut-off Thresholds (Target in Russell 3000 Universe): January 2001 – March 2017



Source: S&P Global Market Intelligence Quantamental Research. Data as at 09/30/2017
Hit rates and significance levels for different cut-off points for the 4-factor model (first panel) and benchmark model (second panel). For readability reasons, we start at a cut-off point of 0.58. The baseline hit rate used for calculating p-values for both models is 13%.

3. Event Study

We used an event study[8] to examine returns to targets and acquirers on announcement and cancelation dates. For liquidity reasons, we require both targets and acquirers to be members of the Russell 3000 universe on the announcement date.

All excess or abnormal returns are calculated after controlling for market, value, size and momentum risk factors. Returns are winsorized to three standard deviations.

3.1. Excess Returns on Announcement Date

Targets typically outperform around deal announcements (Table 3), similar to what has been documented in the literature. In the pre-announcement window, we report an average excess return of 0.65% (statistically significant at the 10% level), with a 53% hit rate. The average excess return to targets two days before and one day after the announcement date

[8] An event study is used to measure the immediate impact of an event on the value of a firm. See Appendix D for methodology used.

is 7.79% with a hit rate of 84%, both significant at the 1% level. The return magnitude is much smaller for acquirers, with the only significant return one day after event date (-0.26%).

Table 3: Canceled Deals: Excess Returns to Targets & Acquirers on Announcement Dates (January 2001 – March 2017)

Excess Returns to Targets & Acquirers on Anouncement Date						
	Target in Russell 3000			Acquirer in Russell 3000		
Event Window	Average	Hit Rate	Count	Average	Hit Rate	Count
Pre-Announcement Window (t-7,t-2)	0.65%*	53%	314	0.13%	49%	824
2 Days Before to 1 Day After Event Day (t-2,t+1)	7.79%***	84%***	314	-0.30%	47%*	824
Event Day Return (t-1,t0)	3.98%***	78%***	314	-0.09%	49%	824
1 Day Forward Return (t+0,t+1)	1.33%***	57%**	314	-0.26%**	47%*	824

*** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 09/30/2017.

3.2 Excess Returns on Canceled Date

The average excess returns and hit rates to targets are negative and statistically significant for all short-term return horizons (Table 4). Bid announcement returns over the [t-2, t+1] window (7.79%) are only partially reversed at termination date (-3.35%). The initial offer by the acquirer can provide additional information to investors about the value of the target. This may be reinforced if the target rejects the initial offer (or provides a counter offer) as a tactic to encourage a higher revised offer or bids from other suitors.

Table 4: Canceled Deals: Excess Returns to Targets & Acquirers on Canceled Dates (January 2001 – March 2017)

Excess Returns to Targets & Acquirers on Cancelled Date						
	Target in Russell 3000			Acquirer in Russell 3000		
Event Window	Average	Hit Rate	Count	Average	Hit Rate	Count
Pre-Announcement Window (t-7,t-2)	-1.30%***	37%***	257	-0.15%	49%	793
2 Days Before to 1 Day After Event Day (t-2,t+1)	-3.35%***	38%***	257	0.15%	51%	793
Event Day Return (t-1,t0)	-1.31%***	42%***	257	0.02%	52%	793
1 Day Forward Return (t+0,t+1)	-1.30%***	41%***	257	0.04%	50%	793
1-month Forward Return	-1.72%*	46%	239	0.01%	47%*	791
3-months Forward Return	-2.48%*	44%	235	-0.22%	46%**	783
6-months Forward Return	0.33%	50%	230	-0.86%	47%*	775

*** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 09/30/2017.

For targets, results over the long-term return horizon indicate that most of the price impact occurs around cancelation date, as the average excess returns over the 1-3 month window is only significant at the 10% level. Acquirers do not benefit from terminated deals as the excess returns to bidders around and subsequent to termination date are not significant.

4. Data

This research leverages S&P Global Transactions M&A package and S&P Global Professionals package. The M&A Transactions package provides detailed data for merger and acquisition transactions. Coverage is global and includes specifics such as deal status, features, advisers, conditions, buyer, seller, target information as well as complete consideration history and amounts. Data is available for the U.S from 1998 and for Australia, Europe, the Middle East and Africa from 2001. Coverage for both Asia and Latin America starts in 2006.

The Professionals package profiles professionals with current and prior company/board affiliations. Data includes biographies, job functions, titles, education, and dates of birth. This was the source of the title, age and company for CEOs used in our analysis.

5. Conclusion

Predicting deals that are likely to be canceled is of interest to both M&A advisers and equity investors. Our research shows that factors that increase the probability of deal cancelation include size, deal proportionality, perceived price discount, CEO age and regulatory risk.

The hit rate for a group of deals classified as "high termination risk" by our 4-factor model is 26%, twice the hit-rate of random chance**.** The 4-factor model also has higher cancelation hit rates than a market-based benchmark model, with the difference in hit rate between both models statistically significant at the 1% level (for a subset of probability cut-off values).

Our event study confirms the return pattern to both targets and acquirers documented by academia. The short term impact to targets following deal cancelation is negative (-3.35%), although the long-term impact is muted. Equity investors should consider this price impact and the probability of the deal going through, if they currently hold, or plan on adding a stock that has been targeted for acquisition to their portfolio.

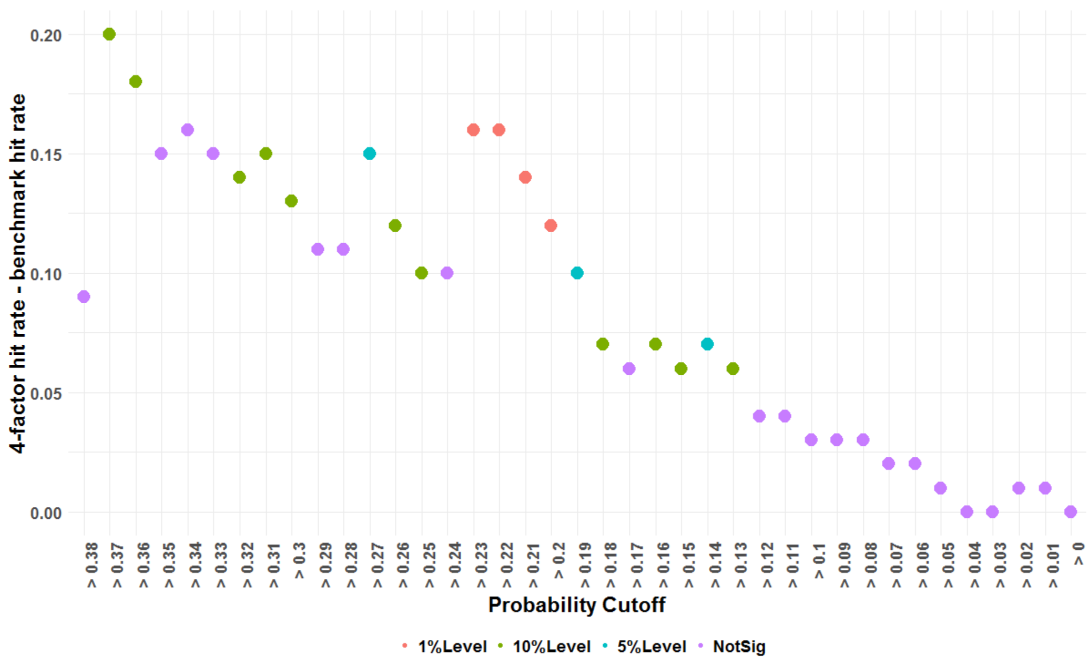
Appendix A (List of Factors Tested)

Candidate Predictor	Mnemonic	Type
Year on Year Sales Growth	yoyGrwSales	Fundamental
Return on Assets (Net Income / Total Assets)	ROA	Fundamental
Earnings Yield (Earnings per Share / Stock Price)	earnYield	Fundamental
Book Leverage (Assets / Equity)	bookLev	Fundamental
Log of Total Assets	logTotalAssets	Size
Log of Market Cap	logMarketCap	Size
Log of Revenue	logRevenue	Size
Target's Market Cap / Acquirer's Market Cap	tgtAcqMktCap	Deal Proportionality
Transaction Size (Announced Deal Size / Market Cap of Acquirer)	transactionSize	Deal Proportionality
Perceived Price Discount	priceTo52WHigh	Technical / Price Trend
12-month Price Momentum	priceMOM	Technical / Price Trend
2-month Price Change	shortTermMom	Technical / Price Trend
Target & Acquirer in same sector (Binary Indicator)	tgtAcqSect	Regulatory Risk
Target & Acquirer in same sub-industry (Binary Indicator)	tgtAcqSubInd	Regulatory Risk
Sum of Target & Acquirer Market Cap Divided by Sector Market Cap	mktCapTgtAcqToSect	Regulatory Risk
Sum of Target & Acquirer Market Cap Divided by Sub-Industry Market Cap	mktCapTgtAcqToSubInd	Regulatory Risk
Sum of Target & Acquirer Total Asset Divided by Sector Total Asset	assetsTgtAcqToSect	Regulatory Risk
Sum of Target & Acquirer Total Asset Divided by Sub-Industry Total Asset	assetsTgtAcqToSubInd	Regulatory Risk
Both Acquirer & Target in Highly Regulated Industry (Binary Indicator)	regIntensity_both	Regulatory Risk
Acquirer in Highly Regulated Industry (Binary Indicator)	regIntensity_acq	Regulatory Risk
Target in Highly Regulated Industry (Binary Indicator)	regIntensity_tgt	Regulatory Risk
30-Day Bid Premium (Based on Target's Price 30 days Prior to Event Date)	bidPremium30Days	Deal Characteristics
7-Day Bid Premium (Based on Target's Price 7 Days Prior to Event Date)	bidPremium7Days	Deal Characteristics
Trading Premium (Offer Price - Trading Price 1-Day After Announcement / Trading Price 1-Day After Announcement)	tradePremium	Deal Characteristics
All Stock Deal (Binary Indicator for all Stock Deal)	allStock	Deal Characteristics
All Cash Deal (Binary Indicator for all Cash Deal)	allCash	Deal Characteristics
Percentage Cash	percentCash	Deal Characteristics
Deal Approach (solicited vs unsolicited)	dealAppr	Deal Characteristics
Deal Attitude (hostile vs friendly)	dealAtt	Deal Characteristics
CEO Age - Binary Indicator (Male CEOs less than 50 years old)	CEOage	Executive Characteristic

Appendix B

The figure below shows the p-values of the 4-factor model's cancelation hit rate, using the hit-rate of the benchmark model as the baseline for calculating p-values. The y-axis is the difference in cancelation hit rate between the 4-factor and benchmark model (positive values indicate 4-factor model has a higher cancelation hit rate).

Difference between 4-factor and benchmark model cancelation hit rates (Target in Russell 3000 Universe): January 2001 – March 2017



Appendix C

Mathematically, the values of the benchmark model are derived as follows:

Benchmark model cancelation probability = 1 – implied market closing probability

Where,

Implied market closing probability = Portion of offer spread realized / Offer spread

Portion of offer spread realized = target's stock price 1 day after announcement – target's stock price 1-month prior to announcement

Offer spread = offer price – target's stock price 1-month prior to announcement

The following steps describe the process:

1. Calculate the **offer spread** as the difference between the offer price and the target's stock price 1-month prior to deal announcement.
2. Calculate the **portion of the offer spread** realized as the target's price 1 day after deal announcement minus the target's stock price 1-month prior to deal announcement.
3. Divide step 1 by step 2
4. If either step 1 or step 2 yields a negative value, the benchmark probability score for that deal is 0. There is a high probability of the deal not closing since either the offer price is below the stock's price 1-month ago (step 1) or the target's stock price 1 day after deal announcement is below its trading price 1-month ago (step 2).
5. If step 4 yields a value larger than 1, cap it at 1. A value larger than 1 indicates that the stock is trading above its offer price.
6. To make the probability values in step similar in direction to the model, transform the score in step 5 by taking the difference between 1 and the output of step 5.

Appendix D (Event Study)

Since the intent is to examine price action around announcement and cancelation dates, we applied the following filters to remove the impact of confounding events[9]:

- Exclude observations where the canceled date of a transaction lies between the announced and closed date of another successful bid.
- For ex-post returns (returns after the canceled date), exclude a target if the target is the subject of another bid during the return calculation window.

[9] Our results are qualitatively similar if we do not apply both filters.

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Our Recent Research

January 2018: U.S Stock Selection Model Performance Review

Starting with the U.S. Election in November 2016, the S&P 500 Index has registered 14 consecutive months of positive returns. Only once has the S&P 500 had a longer run of positive returns since 1959. Coincident with strong equity returns, U.S. stocks began to trade on the basis of their own idiosyncratic factors, as opposed to sector or common factor risk.

All 4 of our U.S strategy models returned positive long-only returns in 2017. This report reviews the performance of all 4 models during the year.

September 2017: Natural Language Processing - Part I: Primer

Given the growing interest in NLP among investors, we are publishing this primer to demystify many aspects of NLP and provide three illustrations, with accompanying Python code, of how NLP can be used to quantify the sentiment of earnings calls. The paper is laid out into four sections:

- **What is NLP:** We demystify common NLP terms and provide an overview of general steps in NLP.
- **Why is NLP Important:** Forty zettabytes (10^21 bytes) of data are projected to be on the internet by 2020, out of which more than eighty percent of the data are unstructured in nature, requiring NLP to process and understand
- **How can NLP help me:** We derive insights from earnings call transcripts measuring industry-level trends or language complexity.
- **Where do I start:** Code for each use is enclosed, enabling users to replicate the sentiment analysis

July 2017: Natural Language Processing Literature Survey

In client conversations, Natural Language Processing (NLP) and the analysis of unstructured data is a topic of regular conversation. S&P Global Market Intelligence offers several unstructured datasets garnering market attention. The first is earnings call transcripts, with unique speaker id's to identify who is speaking on the call. The second data set is the text content in the 10-K. In advance of a publication of Quantamental primer on NLP next month which will take readers through the process of handling unstructured data and generating sentiment scores, we offer this literature survey. What follows are ten papers that the team has identified as being of particular interest to investors on this topic.

June 2017: Research Brief: Four Important Things to Know About Banks in a Rising Rate Environment

With the Fed signaling further rate hikes ahead, bank investors may want to know which investment strategies have worked best in a rising rate environment historically. This paper leverages our empirical work on the SNL Bank fundamental data to aid investors in selecting bank stocks as rates rise.

April 2017: Banking on Alpha: Uncovering Investing Signals Using SNL Bank Data

This study leverages S&P Global Market Intelligence's SNL Financial data to answer three questions of importance to bank investors: 1. Which widely-used investment strategies have historically been profitable? 2. Which lesser-known strategies deserve wider attention? 3.

How do these strategies perform across varying macro environments: rising vs. falling interest rates and above- vs. below-average financial stress?

March 2017: Capital Market Implications of Spinoffs
Spinoff activities have picked up in recent years. In 2015, more than $250 billion worth of spinoff transactions were closed globally - the highest level in the last 20 years. This report analyzes the short- and long-term performance of spun-off entities and their parent companies in the U.S. and international markets. We also examine a related but distinct corporate restructuring activity – equity carve-outs, which separate a subsidiary through a public offering.

January 2017: U.S. Stock Selection Model Performance Review 2016

November 2016: Electrify Stock Returns in U.S. Utilities

October 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 2

September 2016: A League of their Own: Batting for Returns in the REIT Industry - Part 1

August 2016: Mergers & Acquisitions: The Good, the Bad and the Ugly (and how to tell them apart)

July 2016: Preparing for a Slide in Oil Prices -- History May Be Your Guide

June 2016: Social Media and Stock Returns: Is There Value in Cyberspace?

April 2016: An IQ Test for the "Smart Money" – Is the Reputation of Institutional Investors Warranted?

March 2016: Stock-Level Liquidity – Alpha or Risk? - Stocks with Rising Liquidity Outperform Globally

February 2016: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2015

January 2016: What Does Earnings Guidance Tell Us? – Listen When Management Announces Good News

December 2015: Equity Market Pulse – Quarterly Equity Market Insights Issue 6

November 2015: Late to File - The Costs of Delayed 10-Q and 10-K Company Filings

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