Global Markets Research

Quantitative Strategy

Deutsche Bank

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Signal Processing

Targeting Takeovers

Research Summary
We build a quant model for predicting takeover targets. A novel feature of our model is the use of informed trading variables, constructed using high frequency and options data, which help us enter potenial targets at the right time.

A quant model for predicting potential takeover targets

M&A is back in style
The recent decline in equity valuations, coupled with cash-heavy U.S. corporate balance sheets, has triggered a renewed interest in M&A activity. In this report we build a quantitative model to predict potential takeover targets.

Overcoming the loser's drag
We find that takeover targets tend to be "loser" companies on average, i.e. companies with weak earnings, poor growth prospects, higher volatility, and underperforming share prices. This is problematic because it means our takeover prediction model has to tilt towards these undesirable characteristics. A key focus of our research is how we can overcome this performance drag.

Follow the smart money
Another challenge when predicting takeovers is getting the timing right. A potential takeover candidate can easily underperform for an extended period before getting taken over, so getting in too early can be dangerous. Our solution is to use a novel set of "informed trading" variables – derived from high frequency, options, and new sentiment data – to refine the timing of the buy decision.

Screening for takeover targets
We also include a screen listing our top 30 potential takeover targets, as predicted by our model. Top picks include: Tenet Healthcare, Conagra Foods, Windstream Corp., Frontier Communications, and Dean Foods.

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Stock screen

Potential takeover targets

We screen the S&P 500 universe for potential takeover targets

Based on the methodology described in this report, the screen below lists potential takeover targets in the S&P 500 universe. For a complete ranking of stocks in the entire Russell 3000 universe, please contact us at DBEQS.Americas@db.com or 212-250-8983.

Note that these takeover candidates are selected using a purely quantitative process which makes no reference to hurdles due to legal or regulatory issues, or unique capital structures (e.g. poison pills). Therefore investors should use this screen as only one input when selecting potential takeover candidates.

Figure 1: Potential takeover targets based on DB Quant Takeover Target screen

Ticker	Name	Sector	DB Takeover Score (higher = more likely to become takeover target)
THC	TENET HEALTHCARE CORP	Health Care	0.34
CAG	CONAGRA FOODS INC	Consumer Staples	0.27
S	SPRINT NEXTEL CORP	Telecommunication Services	0.26
WIN	WINDSTREAM CORP	Telecommunication Services	0.25
PCS	METROPCS COMMUNICATIONS INC	Telecommunication Services	0.21
FTR	FRONTIER COMMUNICATIONS CORP	Telecommunication Services	0.21
DF	DEAN FOODS CO	Consumer Staples	0.20
BSX	BOSTON SCIENTIFIC CORP	Health Care	0.20
AMT	AMERICAN TOWER CORP	Telecommunication Services	0.19
ETFC	E TRADE FINANCIAL CORP	Financials	0.15
EP	EL PASO CORP	Energy	0.15
CSC	COMPUTER SCIENCES CORP	Information Technology	0.15
SO	SOUTHERN CO	Utilities	0.14
LXK	LEXMARK INTL INC -CL A	Information Technology	0.14
NVLS	NOVELLUS SYSTEMS INC	Information Technology	0.13
MPC	MARATHON PETROLEUM CORP	Energy	0.12
COG	CABOT OIL & GAS CORP	Energy	0.12
TLAB	TELLABS INC	Information Technology	0.12
ISRG	INTUITIVE SURGICAL INC	Health Care	0.11
CTL	CENTURYLINK INC	Telecommunication Services	0.11
PBCT	PEOPLE'S UNITED FINL INC	Financials	0.11
SVU	SUPERVALU INC	Consumer Staples	0.11
RRC	RANGE RESOURCES CORP	Energy	0.11
CPWR	COMPUWARE CORP	Information Technology	0.11
EQT	EQT CORP	Energy	0.11
VZ	VERIZON COMMUNICATIONS INC	Telecommunication Services	0.10
ABC	AMERISOURCEBERGEN CORP	Health Care	0.09
SYMC	SYMANTEC CORP	Information Technology	0.08
BIIB	BIOGEN IDEC INC	Health Care	0.08
BRCM	BROADCOM CORP	Information Technology	0.08

Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

A letter to our readers

A quant approach to takeover prediction

We build a quant model for predicting likely M&A targets

The market sell-off in recent weeks, coupled with cash-heavy U.S. corporate balance sheets, has triggered a renewed interest in M&A activity. Indeed, the number of M&A transactions has been rising steadily since the depths of the credit crisis, and this year there have already been over 100 takeover transactions among Russell 3000 stocks. For investors, the idea that one might be able to forecast potential takeover targets is, needless to say, an attractive one. On average, Russell 3000 takeover targets generate an announcement day return of 15-20%, so even if one could correctly pick just a few potential takeover candidates each quarter, the upside would appear to be substantial. However, like everything in finance, there is no free lunch.

Overcoming the loser's drag

The problem with holding a portfolio of potential M&A stocks is they tend to be "loser" stocks

Unsurprisingly, we find that potential takeover targets tend to be "loser" companies on average, i.e. companies whose shares have underperformed in the long run. They also tend to be smaller cap companies with weak earnings, poor growth prospects, and higher volatility. This presents a challenge to quant investors, because typically these are all characteristics that quant models try to avoid. In other words, chasing potential takeover targets involves systematically tilting one's alpha model towards these undesirable characteristics. As a result, a key focus of our research is to show how we can remove some of this downside drag, whilst still harvesting some of the upside when we do get a takeover prediction right.

It's all in the timing

Another vexing issue in takeover prediction is timing; a stock may underperform for a long period of time before becoming a takeover target. This is closely related to the "loser's drag" mentioned above. The risk is that even if our model is eventually right, we might sacrifice too much performance holding the stock on the way down while we wait for our call to materialize. As the infamous saying goes, being early and right is the same as being wrong.

Follow the smart money

We use "informed trading" metrics to improve the timing of the buy decision

Our solution to this timing problem is to introduce shorter-term, "informed trading" variables. The idea is to detect abnormal trading activity in a stock, using unique metrics like options activity and the intraday pattern of high frequency trades. Our research shows that these variables can help our model get into potential takeover candidates closer to their actual takeover date, and hence avoid some of the negative drag associated with holding "loser" stocks.

Of course, we certainly aren't the first to build an M&A prediction model – both academics and practitioners have been researching and using such models for decades[1] – but we do think our model has some novel features that can help overcome the hidden performance drags in takeover forecasting.

Regards,

Yin, Rocky, Miguel, Javed, and John
Deutsche Bank North American Equity Quantitative Strategy

[1] For example, our colleagues in our Equity Strategy team have been running a successful M&A prediction model for some time. For more information see: Chadha, B., P. Thatte, and K. Parker, 2009, "M&A: Buy acquisition targets", *Deutsche Bank US Equity Strategy*, 20 October 2009.

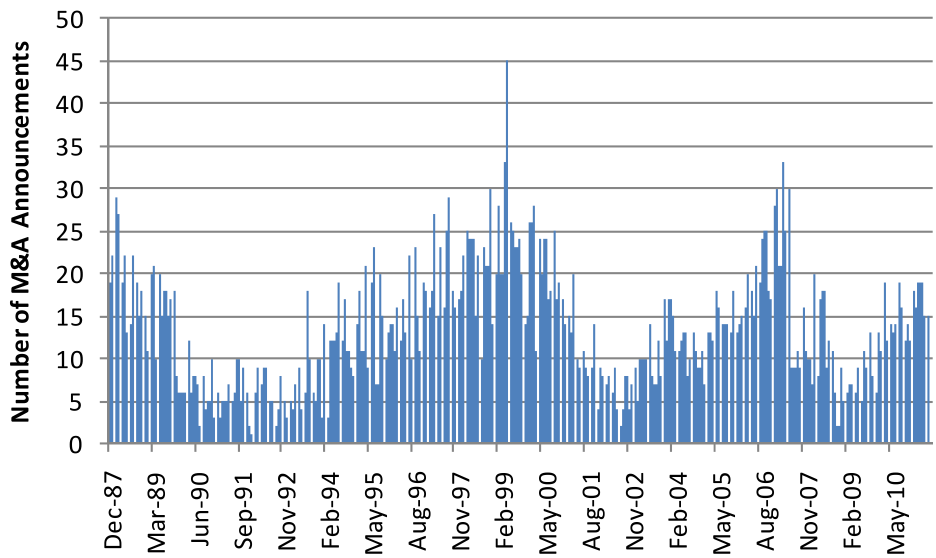
The fingerprint of a takeover target

Setting the scene

M&A activity has been rising steadily since the credit crisis

On average over the past 25 years there have been around 15 takeover announcements per month for stocks in the Russell 3000 universe. Of course, this long-term average hides significant cyclicality; as Figure 2 shows, M&A transactions tend to occur in waves that are roughly correlated with the performance of the equity market. Since bottoming out in the middle of the credit crisis, the number of deals has been rising steadily again.

Figure 2: Number of M&A announcements, Russell 3000 constituents



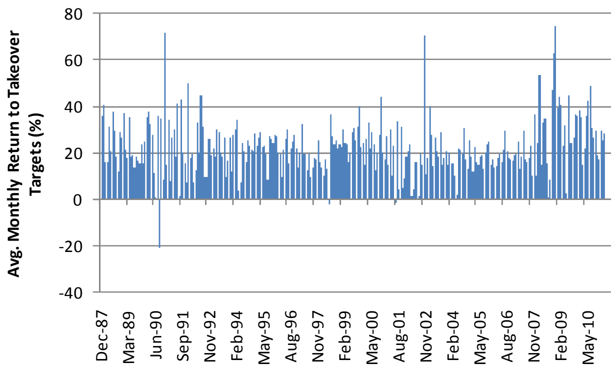
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Significant upside, but can we capture it?

Announcement day returns for takeover targets are large

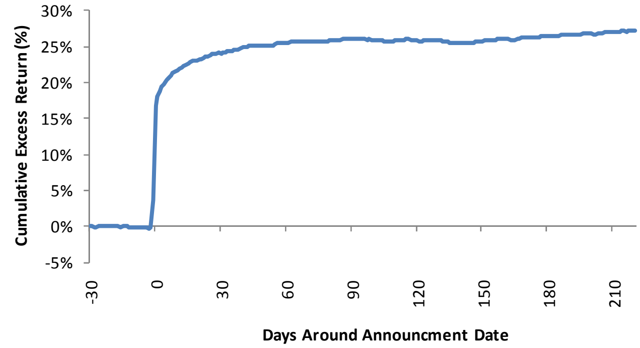
Figure 3 shows the average return for stocks that are announced as takeover targets each month. Over the long-run the average is 20% and in recent years has been even higher. In Figure 4 we show an event study of the average excess returns for takeover targets around the announcement date. Both charts illustrate the potential upside to a takeover prediction model, even if we can only capture a small fraction of these returns.

Figure 3: Average monthly returns to takeover targets, Russell 3000 constituents



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 4: Median excess returns for S&P 500 takeover targets around announcement date



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We use Thomson Reuters SDC Platinum as our source for M&A transactions

In this report, we use the Thomson Reuters SDC Platinum database as our source for M&A announcements. This database covers around 680,000 global M&A transactions from 1977 onwards, split between around 222,000 U.S. transactions and 458,000 international deals. For our research, we limit our analysis to takeover announcements that occur after 1987 (to line up with the start of our fundamental database) and where the target company is a member of the Russell 3000 at the time of the takeover. We also remove takeovers where the acquirer is seeking less than 50% ownership, and where the deal value is less than $25 million. Importantly, we include all announced deals, regardless of whether the deal is completed or not. This is to avoid look-ahead bias; when the deal is first announced we of course do not know whether it will be successful or not.

Figure 5 shows a snapshot of the database. In this particular example, the highlighted row refers to the recent announcement that Google is seeking to acquire Motorola Mobility.

Figure 5: Snapshot of Thomson Reuters SDC database

DATE_ANN	STATUS	TGT_SEDOL	TGT_NAME	ACQ_SEDOL	ACQ_NAME	VALUE_TRANSACTION
16-AUG-11	Pending	2108719	Renaissance Learning Inc	(null)	Raphael Acquisition Corp	436.048
15-AUG-11	Pending	B4NHDJ5	Motorola Mobility Holdings Inc	B020QX2	Google Inc	11877.584
15-AUG-11	Pending	2262530	Republic Services Inc	2262530	Republic Services Inc	750
09-AUG-11	Pending	B3PQ520	Starwood Property Trust Inc	B3PQ520	Starwood Property Trust Inc	100
07-AUG-11	Pending	2900614	Transatlantic Holdings Inc	(null)	National Indemnity Co	3249.157
04-AUG-11	Pending	B3X6B24	Emdeon Inc	(null)	Blackstone Capital Partners VI	2200.521
03-AUG-11	Pending	B1214K5	Global Traffic Network Inc	(null)	GTCR Gridlock Acquisition Sub	266.702
02-AUG-11	Pending	2008121	AMAG Pharmaceuticals Inc	(null)	MSMB Capital Management LLC	380.879
01-AUG-11	Pending	B07XD68	PAETEC Holding Corp	B0650W0	Windstream Corp	2228.134
01-AUG-11	Pending	2434050	HearUSA Ltd	(null)	Audiology Distribution LLC	129
29-JUL-11	Pending	2904155	Allied Healthcare Intl Inc	(null)	Saga Group Ltd	169.928
27-JUL-11	Pending	2825052	Alliance Bankshares CorpVA	2648055	Eagle Bancorp IncBethesdaMD	31.23
26-JUL-11	Intended	2297026	S1 Corp	2889155	ACI Worldwide Inc	526.023
22-JUL-11	Completed	B570041	Continental Resources Grp Inc	(null)	Continental Resources Acq Sub	67.537
21-JUL-11	Pending	2954019	Medco Health Solutions Inc	2326469	Express Scripts Inc	29370.067

Source: Thomson SDC, Deutsche Bank

Harnessing the power of informed traders

In addition to the traditional fundamental variables, we include a set of unique variables

Having secured M&A transaction data, the other required ingredient is a set of explanatory variables that we can use to predict likely takeover targets. Surveying the academic literature, there are a large number of potential variables we might choose. For example, Brar, Giamouridis, and Liodakis [2009] suggest variables that measure firm size, undervaluation, management efficiency, financial leverage, age, and industry barriers to entry can be useful in determining future takeover probability. These types of variables certainly make intuitive sense, and indeed they will form the foundation of our model (which we will expand on below).

Academic research has found promising prediction power in options and high frequency factors

New directions in academia

However, the recent academic literature – as well as our own research – has started to move in some exciting new directions. Foremost among these is the use of what we might call "informed trading" proxies, as a way of detecting events or the impact of events before the rest of the market. For example, Jin, Livnat, and Zhang [2011] showed that information from the options market can help predict the abnormal return drift after events like earnings announcements, M&A transactions, product announcements, and so on.[2] In other words, by following the trading of "informed" players, we can potentially get a jump on the rest of the market.

Another fascinating recent paper is one by Humphery-Jenner [2011].[3] In his research, the author explores the use of high frequency variables to predict takeover targets. The idea is to use the intraday trading patterns in stocks to try to determine when there is heavier informed trading, which in this case is measured through various metrics related to tick-by-tick trading intensity or the abnormal intraday volume profile. Again, the results are promising: the paper finds that these high frequency variables can be used to predict takeovers, and more importantly, the predictive power survives even when controlling for the more traditional fundamental variables, like valuation and size.

In our own research, we have also explored the use of "informed trading" metrics

Leveraging our own research

Similarly, in our own research we have touched on both these angles. In Cahan et al. [2010a] we showed that information from the options market does appear to lead the stock market, while in Cahan et al. [2010c] we found that a factor called the Residual Probability of Informed Trading (RPIN) – derived from high frequency data – is a consistent predictor of month-ahead stock returns.

Finally, in Cahan et al. [2010b], we studied the use of natural language processing techniques to quantify the textual information in financial news stories. In the context of takeover prediction, a natural extension is to use the volume of news about M&A transactions, at say a sector level, as a predictor of future M&A activity in that sector.

To leverage off these ideas, we consider the metrics listed in Figure 6 as potential explanatory variables for forecasting takeovers. As mentioned, these variables are in addition to the standard fundamental variables (we discuss these in more detail in the next section).

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[2] For our review of this paper, see: Cahan, R. et al., 2011, "Academic Insights: Harnessing the best ideas from academia", *Deutsche Bank Quantitative Strategy*, 25 February 2011

[3] For our review of this paper, see: Cahan, R. et al., 2011, "Academic Insights: Harnessing the best ideas from academia", *Deutsche Bank Quantitative Strategy*, 25 May 2011

Figure 6: Unique variables available for inclusion in DB Takeover Target Model

Variable	Definition	Rationale
Residual PIN (RPIN)	Uses tick-by-tick data to infer the probability of informed trading, controlled for size, volatility, and liquidity. See Cahan et al. [2010c] for the complete definition.	A higher RPIN indicates a stock is being heavily traded by informed traders, which could be the sign of information leakage before a takeover.
O/S Ratio	The ratio of the dollar value of options traded to the dollar value of stock traded, normalized for each stock by the one year history for that stock. See Cahan et al. [2010a] for more information.	Another potential proxy for pre-event informed trading, or information leakage. Abnormally high options volume relative to stock volume can indicate strong directional views being taken by informed traders.
M&A News Volume In Sector	The number of news stories about M&A in a given GICS Level 1 sector, over a trailing window	More market chatter about M&A activity in a particular sector could indicate future takeover activity.
M&A News Sentiment in Sector	The average sentiment (i.e. positivity or negativity) in news stories about M&A in a given GICS Level 1 sector, over a trailing window	More positive sentiment about M&A activity in a particular sector could indicate future takeover activity.
Weibull Shape Parameter	Proposed in Humphery-Jenner [2011]. Detects the presence of high frequency trading by modeling the time until the next trade occurs with a Weibull distribution. In simple terms, a shorter interval between trades means more high frequency trading.	High frequency trading may be another proxy for informed trading activity before an event. If we detect a spike in high frequency trading activity, it may indicate an impending event in the stock.
Intraday Order Imbalance	Proposed in Humphery-Jenner [2011]. The difference between intraday buy and sell volume, as a percent of total daily volume. The determination of which trades are buys and sells is made using the tick test. For more details, see Cahan et al. [2010c].	Could be an early indicator that investors have strong directional views in a particular stock, perhaps a precursor to a takeover event if there has been information leakage.
Intraday Abnormal Turnover	Proposed in Humphery-Jenner [2011]. Measures the deviation of today's intraday volume profile from the "steady state" norm. The deviation is measured as the sum of the absolute difference in volume during each one minute bar today, versus the average volume in that same interval over the past 30 days.	Captures, on a very timely basis, when something "out of the ordinary" is happening in a particular stock.
Intraday Volatility	The standard deviation of 1-minute returns, not including the overnight return	No strong hypothesis.
Intraday Skewness	The skewness of 1-minute returns, not including the overnight return	No strong hypothesis.
Intraday Kurtosis	The kurtosis of 1-minute returns, not including the overnight return	No strong hypothesis.

Source: Humphery-Jenner [2011], Deutsche Bank

A data-driven approach

Our model is based on a logistic regression to forecast a takeover probability

The next question is how we can put everything together to build a predictive model. In the academic literature, the basic building blocks are fairly well established. First, because we are interested in forecasting a binary event – i.e. a stock is either taken over or it isn't – the logistic regression model is the natural choice. Under such a model, the probability that company i will be taken over is given by

$$p_i = \frac{1}{1+e^{-(\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,i}+\ldots+\beta_k x_{k,i})}}$$

where $x_{1,i}, x_{2,i}, \ldots, x_{k,i}$ are company characteristics (e.g. fundamental variables like size and valuation, or unique variables like in Figure 6, or perhaps a combination of both), and $\beta_1, \beta_2, \ldots, \beta_k$ are the corresponding regression coefficients. Like a simple ordinary least squares regression, this model can easily be estimated using historical data. In our case, we would do so by regressing the dependent variable (a binary variable indicating whether a stock is taken over in a given month or not) onto the set of explanatory variables.

Of course, it is never quite so simple. There are two critical issues that need to be addressed when using such a model in practice. First, how can we pick which explanatory variables we should use in the model? We could just pick them all, but this is rarely a good idea. Some variables may be quite correlated, which could lead to multicollinearity. And even if they are not we would still probably end up with an overfitted model that works well in-sample but poorly out-of-sample. Second, how do we handle the fact that we are trying to predict a rare event? Because most stocks never get taken over, a model that forecasts no takeover for every single stock actually does quite well statistically, but is clearly useless in practice.

Data-driven variable selection

We use a backwards stepwise regression to handle variable selection

We solve the first problem, i.e. variable selection, by using an approach we have used before: the backwards stepwise regression.[4] At the start of each year, we take 10 years of trailing data and conduct the step-wise regression. Basically this is a statistical algorithm that starts by overfitting the model (i.e. including all variables) and then iteratively throws out less predictive variables until a smaller, more parsimonious model is reached. We prefer this approach because it avoids the subtle look-ahead bias that is introduced whenever variables are picked ex post (see our more extensive discussion in Luo et al. [2010a]). It also allows the model to evolve slowly over time to capture the fact that the predictive power of variables tends to wax and wane over time. A final benefit is greater flexibility, because it allows variables with different histories to be considered (important in our case because we have much shorter history for the intraday variables).

The rare event conundrum

Our model is estimated over a matched panel, as is common in the academic literature

As mentioned, the fact that takeover events are quite rare is also problematic. Over the past 25 years, only around 15 stocks in the Russell 3000 become takeover targets each month. Therefore a model that simply predicts that every stock has zero probability of being taken over each month will have a fantastic 99.5% hit rate each month. The standard way to deal with this problem in the academic literature is to build a matched sample (see for example Brar et al. [2009]). This is the path we take. The algorithm is as follows:

- Start with the sample of all takeover announcements from 1988-present that meet our criteria (target must be Russell 3000 constituent, deal value > $25m, percent ownership sought > 50%). In total we have 4,004 takeovers in our sample. Each takeover is represented as a firm-date pair, i.e. the stock identifier and the announcement date.
- Randomly select an equal sized pool of non-M&A stocks, with the constraint that the percent of stocks in each calendar year matches that of the M&A sample. For example, in our sample, 4.4% of M&A announcements occurred in 2010. Therefore, in our control sample we assign 4.4% of our random firm-date pairs to random dates in 2010. As a result, our final dataset consists of around 8,000 firm-date pairs, comprising a 50/50 split between M&A and non-M&A stocks, both in the sample overall and in any given year.[5]
- For each firm-date pair, collect the explanatory variables. Low frequency fundamental variables (e.g. price/book, size, etc.) are snapped at the month-end preceding the announcement date (or the randomly assigned date in the case of non-M&A stocks). For higher frequency variables (e.g. intraday abnormal turnover, intraday skewness, etc.) and price-related variables (e.g. price momentum and reversal) we take a five day average of the variable value for the trading days *t*-6 to *t*-1 before the event date. This is to dampen down some of the inherent volatility in these short-term measures.
- At the end of each year from 1997 to 2010, estimate the stepwise logistic regression described above using 10 years of trailing data. The regression coefficients are then used to predict potential takeover targets in the following year.

Putting it all together

Figure 7 summarizes the results of our model estimation – each cell shows the p-value from the regression for a given year. If a cell is grayed out it indicates that factor was not selected by the stepwise regression at that point in time. The rows in the table consist of all potential explanatory variables that could be selected in our model.

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[4] See Luo et al. [2010a] or Luo et al. [2010b] for examples of how we used this technique in stock selection models and style rotation models, respectively.

[5] One reason we like this algorithm is because it gives us another robustness control. We can easily regenerate our entire random no-M&A dataset and then re-run all our results. If our results are robust then the conclusions should be the same over many random control datasets. In unreported results, we find this to be the case.

Figure 7: P-values for coefficients from takeover prediction model

CATEGORY	VARIABLE	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
	(Intercept)	0.05	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.35	0.95
Fundamental	Market Cap	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fundamental	Total Assets	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Fundamental	Dividend Yield	0.06	0.15	0.14											
Fundamental	Earnings Yield		0.00	0.06	0.03	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.04	0.04
Fundamental	Book Yield	0.00	0.01	0.05	0.09	0.12		0.13					0.12	0.14	0.07
Fundamental	Gross Margin	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.01
Fundamental	Net Margin	0.09	0.07	0.05	0.02									0.19	
Fundamental	Sales Turnover					0.08	0.12	0.14							
Fundamental	ROE														
Fundamental	ROA							0.13							
Fundamental	ROIC							0.31							
Fundamental	Interest Cover	0.05					0.15		0.09	0.10					
Fundamental	Debt to Equity Ratio											0.15	0.10	0.16	0.07
Fundamental	Merton Distance to Default	0.06	0.04	0.03	0.05	0.01	0.07	0.04	0.06	0.02	0.05				
Past Performance	1M Total Return	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Past Performance	3M Total Return	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Past Performance	12M Total Return	0.09			0.03	0.06	0.07	0.08	0.09	0.02	0.01	0.01	0.02		
Newsflow	M&A News Sentiment in Sector														
Newsflow	M&A News Volume in Sector													0.05	0.02
Technicals	Abnormal Volume	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Technicals	Daily Volatility	0.10			0.02	0.05	0.05	0.06	0.07	0.02		0.14	0.10	0.05	0.04
Technicals	Daily Skewness		0.14												
Technicals	Daily Kurtosis	0.00	0.00	0.03							0.02	0.02	0.07	0.05	0.01
Informed	Residual PIN													0.13	
Informed	O/S Ratio													0.00	0.00
Informed	Weibull Shape Parameter												0.02	0.10	
Informed	Intraday Order Imbalance														
Informed	Intraday Abnormal Turnover												0.00	0.00	0.00
High Frequency	High Frequency Std. Dev.												0.03	0.08	0.08
High Frequency	High Frequency Skewness												0.00	0.01	0.00
High Frequency	High Frequency Kurtosis														
Sector Dummies	Materials	0.61	0.85	0.90	0.64	0.37	0.26	0.09	0.05	0.01	0.01	0.01	0.02	0.01	0.01
Sector Dummies	Industrials	0.63	0.34	0.54	0.52	0.27	0.14	0.06	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Sector Dummies	Consumer Discretionary	0.50	0.76	0.73	1.00	0.86	0.76	0.23	0.14	0.11	0.04	0.04	0.01	0.00	0.00
Sector Dummies	Consumer Staples	0.76	0.76	0.74	0.98	0.87	0.88	0.90	0.84	0.47	0.16	0.10	0.23	0.29	0.24
Sector Dummies	Health Care	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.11	0.20	0.37	0.61	0.96	0.53	0.63
Sector Dummies	Financials	1.00	0.76	0.73	0.91	0.43	0.31	0.16	0.24	0.26	0.10	0.02	0.00	0.00	0.00
Sector Dummies	Information Technology	0.21	0.68	0.35	0.13	0.12	0.16	0.26	0.49	0.75	0.79	0.66	0.87	0.25	0.30
Sector Dummies	Telecommunication Services	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.02	0.27	0.17	0.08
Sector Dummies	Utilities	0.95	0.86	0.34	0.38	0.70	1.00	0.77	0.55	0.44	0.23	0.18	0.43	0.01	0.04

Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Overall, the results are relatively consistent over time (partly an artifact of our 10 year estimation window) and quite intuitive. Even just eyeballing the table, it is clear that size (measured as market cap and total assets) is quite important (i.e. p-values of close to zero). Recent price performance (one and three month) is also highly significant, as is abnormal trading volume.

The high frequency and options data are highly significant recently

Interestingly, once the high frequency and "informed trading" variables become available (we have a shorter history for these variables) a number of them show up as highly significant, e.g. the O/S ratio, intraday abnormal turnover, and intraday skewness. We will analyze the impact of these unique variables in much greater detail later in this report.

The above table is useful for gauging the importance of the explanatory variables in predicting takeover targets, but it does not tell us the direction. In Figure 8 we show the actual z-statistics for each variable. This allows us to measure the direction in which each variable acts.[6] If the z-score is positive, it means a higher factor score leads to a higher takeover probability.

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[6] The z-statistic is the logistic regression equivalent of the t-statistic in an ordinary least squares regression.

Figure 8: Z-values for coefficients from takeover target model

CATEGORY	VARIABLE	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
	(Intercept)	1.95	2.17	2.89	2.84	4.55	4.37	5.29	5.46	5.60	6.33	5.56	2.48	0.93	-0.07
Fundamental	Market Cap	-8.15	-7.25	-7.94	-7.45	-7.62	-7.80	-7.61	-7.49	-5.99	-6.18	-6.11	-4.29	-4.23	-3.93
Fundamental	Total Assets	7.24	7.39	7.47	6.66	6.30	6.27	6.07	5.41	3.84	3.81	3.87	3.09	3.67	3.43
Fundamental	Dividend Yield	-1.87	-1.45	-1.47											
Fundamental	Earnings Yield		-2.93	-1.86	-2.24	-2.96	-2.86	-2.58	-3.01	-2.99	-2.77	-2.68	-2.47	-2.07	-2.05
Fundamental	Book Yield	-2.91	-2.63	-1.95	-1.69	-1.56		-1.52					1.57	1.46	1.82
Fundamental	Gross Margin	2.80	2.86	3.21	3.11	2.80	3.06	3.17	3.02	2.89	2.47	2.52	2.49	2.26	2.75
Fundamental	Net Margin	-1.71	-1.79	-1.96	-2.33									-1.30	
Fundamental	Sales Turnover					-1.76	-1.55	-1.46							
Fundamental	ROE														
Fundamental	ROA							-1.51							
Fundamental	ROIC							1.01							
Fundamental	Interest Cover	1.93					-1.44		-1.69	-1.65					
Fundamental	Debt to Equity Ratio											1.43	1.65	1.40	1.83
Fundamental	Merton Distance to Default	-1.88	-2.06	-2.21	-1.95	-2.54	-1.84	-2.04	-1.89	-2.28	-2.00				
Past Performance	1M Total Return	8.55	7.38	7.80	7.88	7.56	7.54	6.86	6.63	6.69	6.55	6.19	5.19	4.06	3.09
Past Performance	3M Total Return	4.75	4.51	4.32	4.79	5.24	5.52	5.67	5.86	5.64	5.68	5.72	4.95	3.98	3.95
Past Performance	12M Total Return	1.71			-2.20	-1.85	-1.81	-1.73	-1.68	-2.26	-2.46	-2.56	-2.29		
Newsflow	M&A News Sentiment in Sector														
Newsflow	M&A News Volume in Sector													1.92	2.30
Technicals	Abnormal Volume	-2.55	-3.42	-3.53	-3.02	-2.61	-3.07	-3.33	-3.79	-4.10	-3.94	-4.21	-4.19	-4.07	-4.95
Technicals	Daily Volatility	-1.62			2.34	2.00	1.97	1.90	1.81	2.39		-1.49	-1.63	-1.93	-2.10
Technicals	Daily Skewness		-1.47												
Technicals	Daily Kurtosis	3.55	3.38	2.20							2.26	2.29	1.81	2.00	2.47
Informed	Residual PIN													-1.52	
Informed	O/S Ratio													3.73	3.90
Informed	Weibull Shape Parameter												-2.34	-1.66	
Informed	Intraday Order Imbalance														
Informed	Intraday Abnormal Turnover												4.22	4.87	4.94
High Frequency	High Frequency Std. Dev.												-2.17	-1.78	-1.73
High Frequency	High Frequency Skewness												3.01	2.57	3.02
High Frequency	High Frequency Kurtosis														
Sector Dummies	Materials	0.52	-0.19	-0.13	-0.47	-0.90	-1.12	-1.69	-1.92	-2.45	-2.69	-2.47	-2.39	-2.54	-2.49
Sector Dummies	Industrials	-0.49	-0.96	-0.61	-0.64	-1.11	-1.47	-1.90	-2.73	-3.03	-3.73	-3.58	-3.48	-4.85	-5.14
Sector Dummies	Consumer Discretionary	0.68	-0.31	-0.34	0.01	-0.17	-0.31	-1.19	-1.48	-1.61	-2.07	-2.04	-2.70	-3.78	-4.50
Sector Dummies	Consumer Staples	0.30	-0.30	-0.34	0.03	0.16	-0.15	-0.12	-0.20	-0.72	-1.42	-1.64	-1.21	-1.06	-1.18
Sector Dummies	Health Care	4.42	3.15	3.25	3.06	2.73	2.34	2.13	1.61	1.27	0.90	0.51	-0.05	-0.63	-0.48
Sector Dummies	Financials	0.00	-0.31	-0.35	0.11	-0.80	-1.02	-1.40	-1.18	-1.12	-1.64	-2.28	-3.06	-4.13	-4.95
Sector Dummies	Information Technology	1.25	0.41	0.93	1.53	1.55	1.40	1.12	0.70	0.32	0.27	0.44	-0.17	-1.14	-1.03
Sector Dummies	Telecommunication Services	3.83	3.69	3.99	3.74	4.01	3.48	3.05	2.81	2.57	2.62	2.30	1.11	1.37	1.76
Sector Dummies	Utilities	-0.06	0.18	0.96	0.88	0.39	0.00	-0.30	-0.59	-0.78	-1.20	-1.35	-0.79	-2.51	-2.09

Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The direction of most of the significant variables makes intuitive sense (and are in line with the academic research), but there are some exceptions. In Figure 9 we summarize the key characteristics of likely takeover targets, based on the current model which was estimated at the end of 2010.

Figure 9: Current characteristics of takeover targets, based on DB's Takeover Target Model

Characteristics	Rationale
Smaller market capitalization	Companies with smaller market cap have a larger pool of potential acquirers. Takeovers of smaller companies are also likely to be easier to finance and face less regulatory hurdles.
Large total assets	This is somewhat counterintuitive given the above result, but keeps in mind our model is a multivariate regression so some of the size effect is captured by the above variable. Essentially this is saying that after controlling for other variables, including size, stocks with a larger asset base are more likely to be taken over. This could be because these companies are trading at a discount to their asset base - see the book value factor.
Expensive relative to earnings yield	Takeover targets tend to be expensive on an earnings basis, probably because they are not fully meeting their earnings potential and hence the denominator in the PE ratio is smaller.
Cheap relative to book yield	On the other hand, takeover targets tend to be cheap on the price to book ratio. This suggests such companies have an attractive asset base for the acquirer that is not being fully valued by the market.
Good gross margin	Companies with good gross margins are more likely to be taken over. This could be because such companies offer plenty of cashflow to help meet the future financing obligations from the takeover financing.
Higher gearing	Takeover targets are more likely to be heavily geared. One hypothesis is that such companies are struggling to meet their debt obligations, and need to be acquired to avoid distress.
Outperformed in last 1 and 3 months	Stocks that become takeover targets tend to outperform in the lead up to the actual announcement. This could be the result of information leakage or pre-event speculation.
Higher volume of M&A news in sector	Stocks in sectors that are "hot" in terms of the volume of news stories about M&A activity tend to have a higher probability of getting taken over.
Lower normalized average daily volume	This is something of a size proxy; stocks with lower trading volume (normalized by the volatility of the volume) tend to be more likely to become M&A candidates.
Lower volatility of daily returns	We don't have an intuitive explanation for this result, other than the conjecture that buyers prefer to acquire companies that have relatively stable returns, perhaps because they see these as lower risk opportunities.
Fat tails in daily returns	Stocks with extreme positive or negative returns have a higher takeover probability. One explanation could be that potential takeover targets are more likely to have extreme jumps if there is speculation about a transaction before the formal announcement.
High abnormal options volume relative to stock volume	Abnormally heavy trading in the options market relative to the stock market is also a warning sign of an impending takeover. Our research has shown that this metric is a good proxy for informed trading.
Abnormal intraday volume pattern	When a stock's intraday volume profile deviates from the norm, it tends to be a signal that something is happening in the name. While it is not always possible to identify the cause behind the shift in trading behavior, the fact that something "out of the ordinary" is happening does lead to a higher chance of a takeover announcement.
Lower intraday volatility	Similar to the daily volatility factor above, stocks are more likely to become M&A targets if they also have lower intraday volatility.
Positive intraday skewness	Stocks with extreme positive intraday returns are more likely to become takeover targets. The rationale is probably similar to the excess kurtosis result at the daily level (see above).

Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

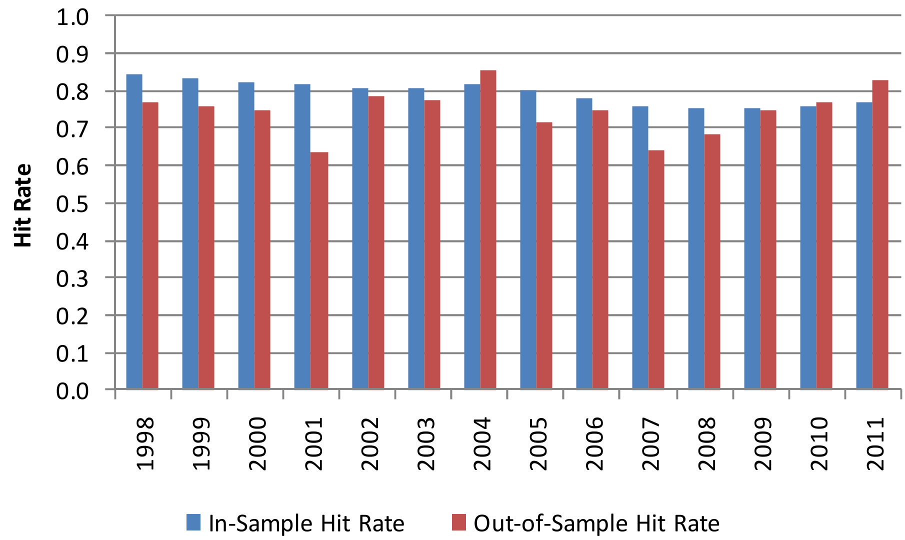
Does it work?

The hit rate of our model, even out-of-sample, is attractive

Our model sounds nice in theory, but the litmus test is how well it works out-of-sample. Figure 10 shows the hit rate (i.e. percent of actual M&A targets in the sample that were correctly predicted), delineated by year and also by the in-sample and out-of-sample period. For example, for 2011 the in-sample bar indicates the hit rate of the model in the 2001-2010 estimation window, and the out-of-sample bar indicates the hit rate in the out-of-sample 2011 calendar year. As we would expect, over time the out-of-sample hit rate is lower than the in-sample hit rate. Nonetheless, the average out-of-sample hit rate over time is still around 75%, which is quite promising.

There is a battery of further diagnostic tests we could employ at this juncture to measure model efficacy – for example ROC curves are commonly used to measure the trade-off between correct predictions and false positives. However, the only measure that we, as investors, really care about is the profitability of our predictions. So rather than measure the success of the model in statistical terms, we prefer to benchmark it in an actual investment setting. In the next section, we provide the details.

Figure 10: Hit rate from takeover prediction model



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

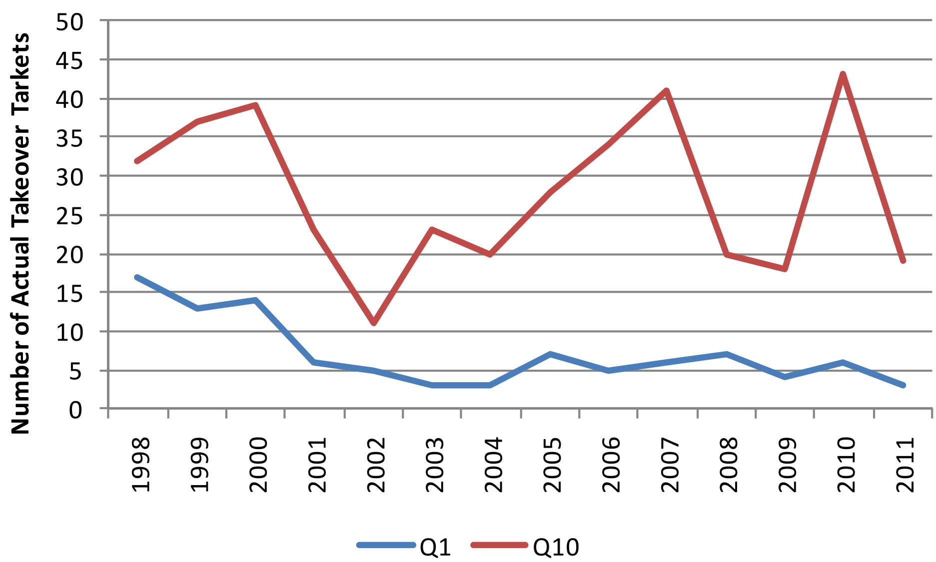
Test driving the model

Real-world hit rates

We believe a more challenging performance hurdle is to use a backtesting context

Unlike the hit rates in the previous section -- which were computed over the matched sample of around 8,000 stocks that we used to estimate the model -- here we focus on the real-world hit rates that an investor would achieve if using the model as the basis of an investment strategy. Suppose at the start of every month we buy the stocks in the top 10% based on the model's forecast takeover probability, and short the bottom 10%. Figure 11 shows the number of actual takeover announcements that would be captured by each portfolio. The results are quite promising – the high takeover probability portfolio (Q10) consistently captures more takeover targets than the low takeover probability portfolio (Q1).

Figure 11: Number of actual M&A targets in decile portfolios, by calendar year



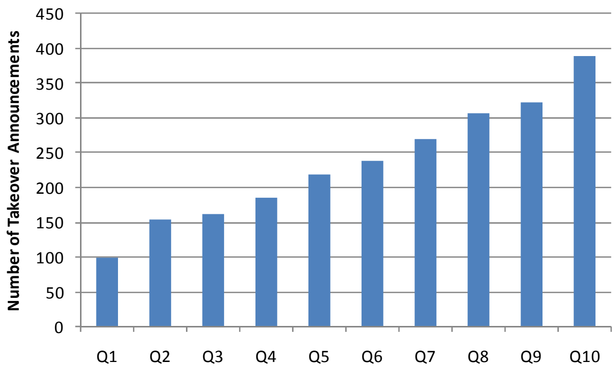
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

A simple top decile portfolio picks up significantly more actual takeovers than a bottom decile portfolio

Figure 12 shows the total number of out-of-sample M&A targets that are picked up by each decile portfolio over the complete backtest (1997 – present). The results are nicely monotonic; had an investor bought stocks with a takeover probability in the top decile at the start of each month he or she would have captured almost 400 announced M&A transactions over the backtest period, compared to only 100 for the bottom decile.

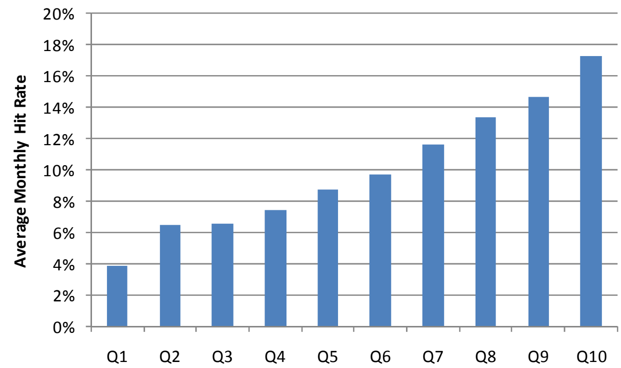
In percentage terms, on average over time the top decile portfolio captures around 17% of all announced takeovers in a given month, compared to 4% for the bottom decile (Figure 13). Again, the pattern is perfectly monotonic, which means the takeover probability forecast from our model does a good job of picking potential M&A targets across the universe.

Figure 12: Number of takeover announcements, by forecast decile



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

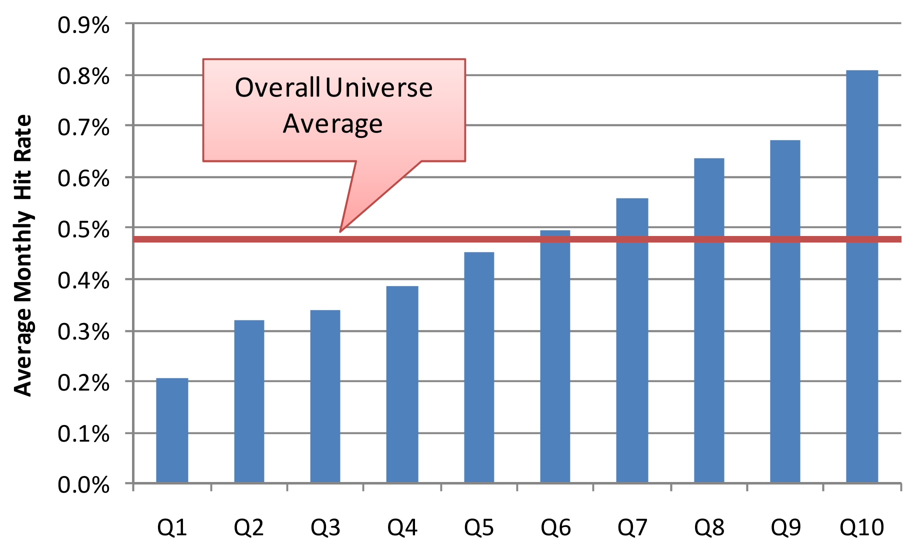
Figure 13: Average hit rate per month, by forecast decile



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

A final chart to consider is Figure 14. This shows the average hit rates from another perspective: what percent of each portfolio ends up becoming a takeover target? For the Russell 3000 universe as a whole, around 15 stocks on average become targets each month. So if we just bought the index, our hit rate would be 15 / 3000 = 0.5%. This is the red line in the chart. In the top decile portfolio, on average each month about 2.4 stocks become takeover targets, i.e. a hit rate of 2.4 / 300 = 0.8%. This is somewhat sobering – even if we focus on the 300 stocks most likely to be taken over (i.e. top decile) we will on average only pick up less than three actual M&A targets per month. The real question is whether this is enough to make any meaningful impact on performance.

Figure 14: Number of actual takeover targets in each decile portfolio, as percent of total portfolio



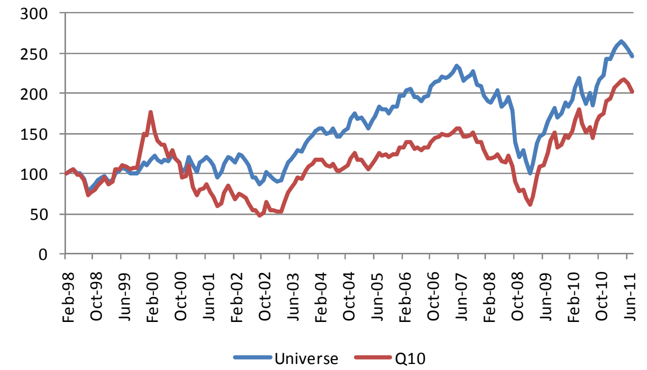
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Performance is what really matters

Hit rates are nice, but what really matters is returns

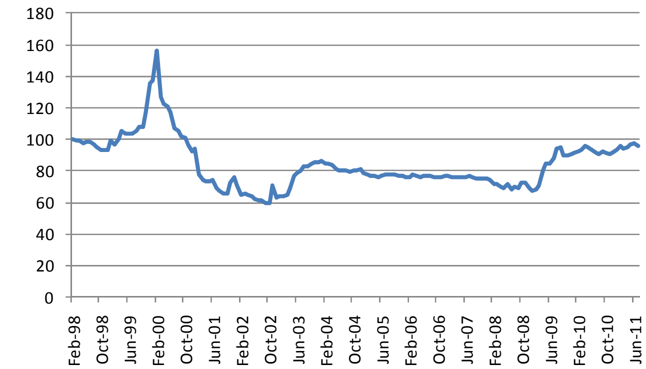
To answer this question, Figure 15 shows the time-series performance of the decile 10 (high takeover probability) portfolio compared to the market. The result is quite disappointing – the high takeover probability portfolio actually underperforms the market over the backtest period. If we look at Figure 16 we can see that most of the underperformance actually comes during the collapse in M&A activity after the dot com boom ended. But even excluding this period the performance of the likely takeover candidates portfolio would be flat at best.

Figure 15: Performance of highest takeover probability portfolio (Q10) and universe



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

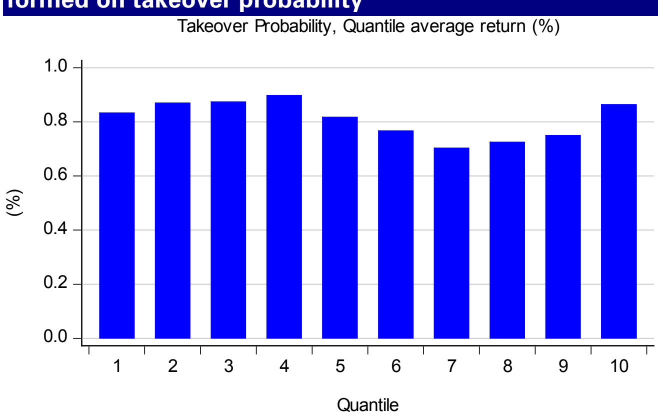
Figure 16: Relative performance of highest takeover probability portfolio (Q10) and universe



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

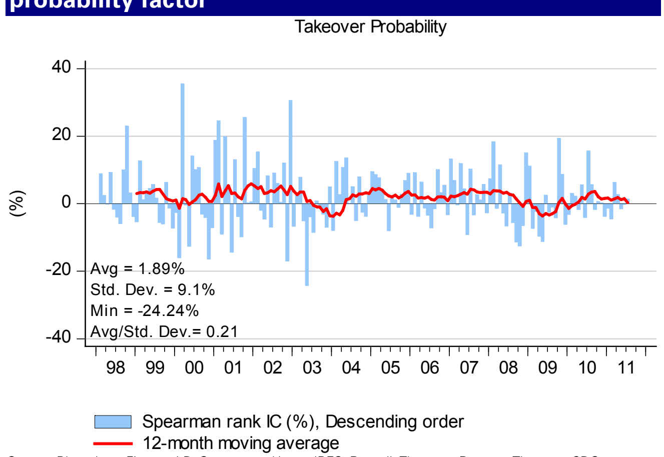
If we look at the average monthly return to each decile portfolio over time (Figure 17), we find that the return profile is quite flat, and if anything stocks with a *lower* takeover probability actually outperform on average (deciles 1 – 4). This is confirmed if we look at the time-series of monthly rank information coefficient (IC) in Figure 18. The direction of the IC is actually "descending" which means that stocks with a lower takeover probability actually outperform those with a higher probability.

Figure 17: Average monthly decile returns to portfolios formed on takeover probability



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 18: Rank information coefficient (IC) for takeover probability factor



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

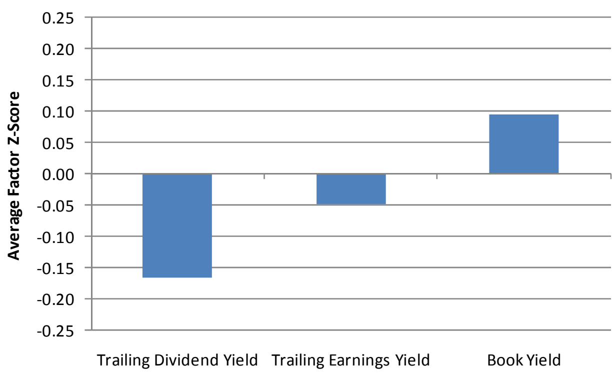
Exposing the exposures

We find takeover targets are highly exposed to undesirable quant characteristics

Needless to say, these results are a little vexing. On one hand we saw that the hit rate of the model is favorable, and monotonic in the right direction. But when we attempt to translate those hit rates into portfolio performance, things fall over. What's going on?

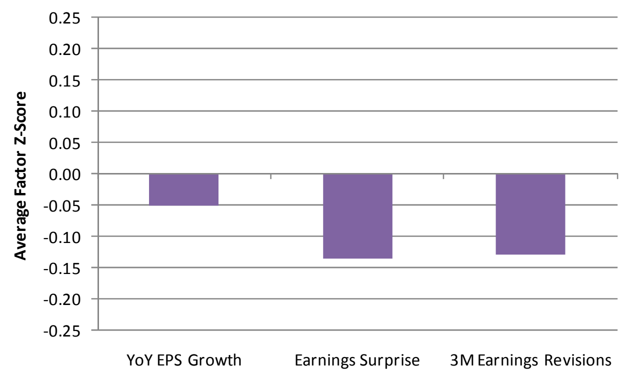
The answer to the riddle lies in the exposures our model is taking when it hunts for potential takeover candidates. In the set of charts below, we focus on the set of stocks that actually become M&A targets, and examine their exposures to common quant factors relative to the universe as a whole. For example, Figure 19 shows the average Value factor z-scores for actual takeover targets, over the period 1997-present. Because the universe at each point in time will, by construction, have an average factor score of 0, this chart is essentially telling us the exposure that M&A stocks have towards the three Value factors listed, relative to the universe. It turns out that on average takeover targets have lower dividend yield, are more expensive on earnings yield, but are cheaper on book yield.

Figure 19: Characteristics of actual M&A targets – Value factors



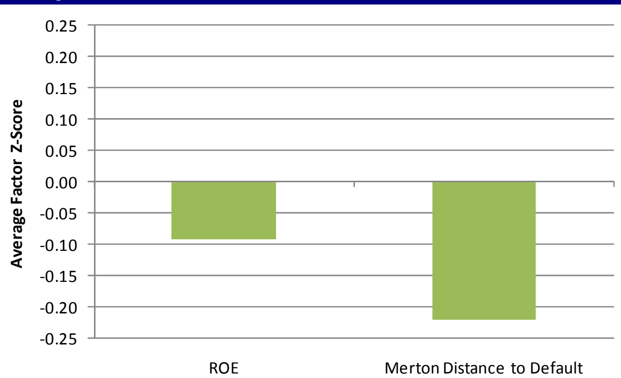
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 20: Characteristics of actual M&A targets – Growth & Sentiment factors



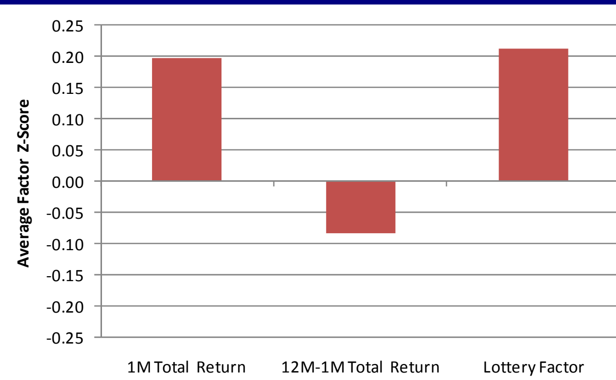
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 21: Characteristics of actual M&A targets – Quality factors



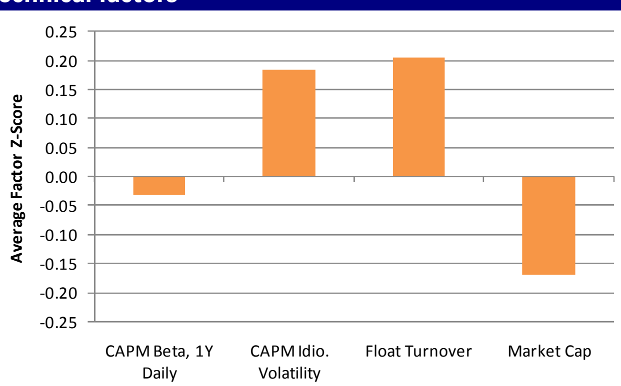
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 22: Characteristics of actual M&A targets – Momentum & Reversal factors



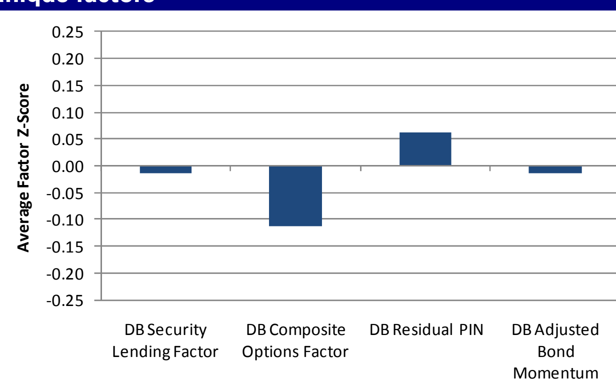
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 23: Characteristics of actual M&A targets – Technical factors



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 24: Characteristics of actual M&A targets – DB unique factors



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Takeover targets tend to have poor growth and stock price performance…

It also turns out that actual takeover targets on average tend to have poor growth prospects and negative earnings momentum (Figure 20). This will come as no surprise, since well performing companies are generally less likely to become takeover targets, given the premium an acquirer would have to pay. We see a similar story in terms of Quality factors; takeover targets tend to have poor ROE and a higher probability of bankruptcy (Figure 22).

…and are lower quality companies that are more likely to go bankrupt

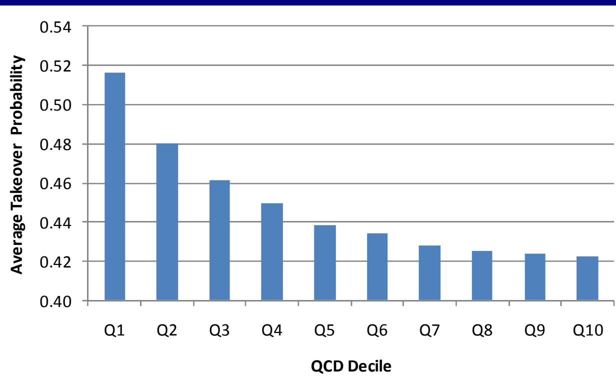
So far this is no surprise; we already saw that our data-driven prediction model also picks up on many of these same characteristics. For example, we saw back in Figure 8 that stocks with short-term outperformance are actually more likely to get taken over. We see the same characteristic in the actual takeover targets -- Figure 22 shows that M&A targets on average have higher 1-month performance, but poor longer-term (12-month) performance.

The bottom line is that stocks that are targeted for takeovers are "loser" stocks on average. And therein lies the problem. Any model that searches for takeover candidates is almost certainly going to tilt towards a set of undesirable characteristics, since these are the stocks most likely to fall victim to a takeover. To reinforce this point, we take our own stock selection model – the QCD model – and look at how it loads up on (1) expected takeover probability, and (2) realized takeover announcements.

As a result, a typical quant model takes an anti-takeover stance

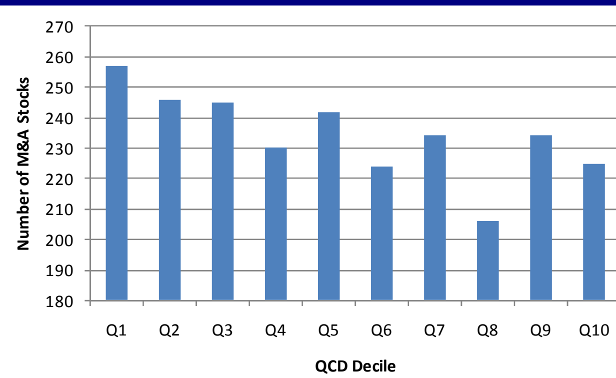
Figure 25 shows the average takeover probability over time for decile portfolios constructed on the QCD model's forecast alpha. In this chart, Q10 are the stocks we expect to outperform in the next month, and Q1 are the stocks expected to underperform. What we find is surprising on face value, but completely understandable if we think about it carefully. What Figure 25 says is that our stock-selection model actually tilts away from potential takeover targets. In other words, our model – which is fully dynamic – decides that the drag from holding loser stocks with a high takeover probability does not pay off in the long run.

Figure 25: Average takeover probability by QCD model decile



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 26: Number of actual M&A stocks by QCD decile



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Similarly, Figure 26 shows the number of actual announced takeovers that each QCD decile portfolio would pick up. Here we find the same result – the QCD model on average is short takeover targets, regardless of whether we are talking about forecast targets or realized targets.

This is the "loser drag" that we alluded to in the introduction. When chasing takeover targets we are making a trade-off: does the extra return from the targets that we correctly forecast outweigh the drag from the false positive loser stocks that we are forced to hold? Unfortunately, so far the evidence suggests no.

The "loser drag" from holding bad stocks can overwhelm the large positive returns from correctly picked takeover targets

To make the arithmetic of this trade-off more concrete, consider Figure 27. This shows a back of the envelope breakdown of the monthly return contribution for the top decile portfolio based on takeover probability (i.e. the most likely takeover candidates, as determined by our model). Because our universe is the Russell 3000, this portfolio will contain around 300 stocks. As shown previously, on average we will correctly identify about 2.4 takeover targets per month within these 300 stocks. The average return for an actual takeover target in the month of the announcement is around 22%, but the average return for a non-M&A stock is -12bps (see the second column in the table). The last column gives the contribution each type of stock makes to the overall monthly portfolio return. Because the percentage of M&A stocks in the portfolio is so small (2.4/300 = 0.8%), the contribution these stocks make to the overall return is small, even though their individual return is high. The bottom line, literally, is that the two return contributions almost cancel out, leaving the portfolio a monthly return that is only marginally positive.

Figure 27: Monthly return contribution breakdown for Decile 10 portfolio

	Number of Stocks	Average Return per Stock (%)	Return Contribution (%)
Decile 10 Portfolio (highest takeover probability)	300		
M&A Stocks Picked Correctly	2.4	21.9	0.18
Non-M&A Stocks	297.6	-0.12	-0.12
Average Monthly Q10 Portfolio Excess Return			**0.06**

Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

What about more concentration?

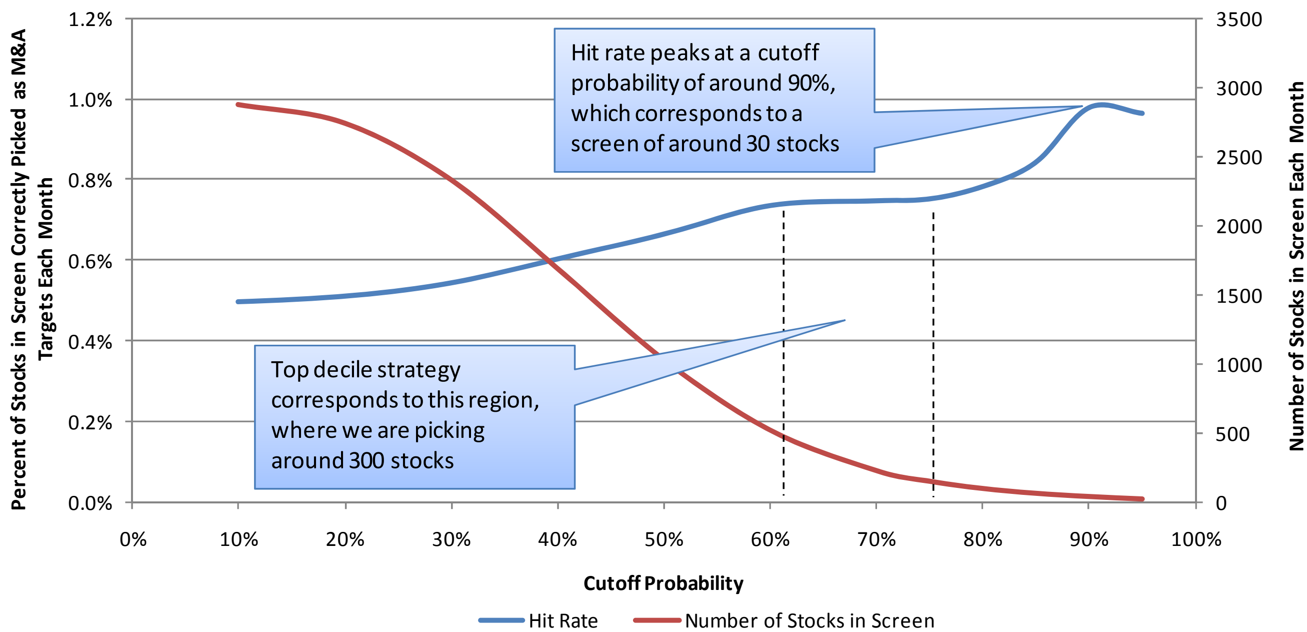
We show that a more concentrated portfolio can help fundamental managers, but not quants

This is just another way of illustrating the problem with all rare-event models: the false positive rate can swamp the few predictions that come true. But there is an obvious question here: why can't we just move to a more concentrated portfolio? Surely if we select fewer stocks, we can increase our hit rate while simultaneously reducing the drag from the large numbers of loser stocks that do not get taken over? Unfortunately, it is not that simple.

In Figure 28 we plot some important metrics as a function of cutoff probability. The cutoff probability is just the threshold above which we assume a stock is a takeover target. For example, if our cutoff probability is 70%, then we assume every stock with a forecast takeover probability greater than 70% is a likely takeover target. The blue line in the chart shows the percent of stocks in our screen each month that we correctly pick as takeover targets, for various levels of cutoff probability.[7] The red line shows the size of our takeover screen or portfolio at each cutoff level. For example, if we form a top decile portfolio, we are implicitly selecting a cutoff probability of around 65-70%, which equates to a 300 stock portfolio (see the red line). If we move to a more concentrated portfolio (i.e. raise the cutoff probability) we can see that we can improve our hit rate further. In fact, from the chart we can see that we can get the "optimal" hit rate by using a cutoff around 90%. In turn, this means a portfolio of around 30-35 stocks.

[7] Note this analysis looks similar to, but is actually quite different from, the standard academic analysis. The problem in the academic literature is that the optimal hit rate is usually determined using the matched sample that is used to estimate the model. This ignores a crucial dimension: time. In the matched panel, stocks appear once, either as a takeover target or not. This means a positive hit, i,e, a correct call, happens if we predict a takeover and a stock is subsequently taken over any time in its life. In a real implementation, we have to measure the hit rate every time we apply the screen, e.g. every month. A positive hit only occurs if we predict a takeover at the start of a month, and the stock is subsequently taken over *in the following month*. This is why the numbers above are much lower than what you see reported in academia.

Figure 28: Average percent of stocks in screen correctly picked as M&A targets each month and average size of screen



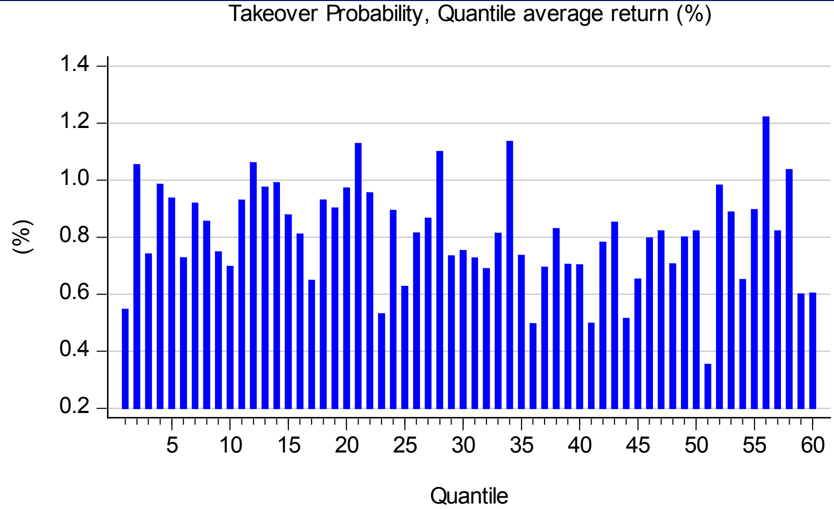
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

On the weight of this evidence it would seem we will be better off if we use a more concentrated portfolio? Yes and no. It really depends on one's goal. If we are seeking a screen that gives us the highest percentage chance of finding takeover targets, then yes, we do want a concentrated portfolio. Investors who fall in this camp might include fundamental investors who are looking for a good screen of potential takeover targets that they can then analyze further. As an aside, this is the reason we choose to include 30 stocks in the screen at the front of this report.

Quants will prefer to maximize expected return, rather than hit rate

However, if we are a quant investor, maximizing the hit rate may not be the ideal goal. The reason being we care more about returns than hit rate. If we are systematically buying a portfolio of likely takeover candidates, we care about the return of the overall portfolio. A higher hit rate is nice to have, but only if hit rate is proportional to returns. It turns out that this is not the case. In Figure 29 we look at the average returns to concentrated 50 stock portfolios. From this it is clear that even if we picked, say, the top 50 stocks based on takeover probability (i.e. the right most bar in the chart) the average returns still would not be very favorable. So even though the hit rate is "more optimal" in the far right bar, this does not equate to better returns.

Figure 29: Average returns to concentrated 50 stock portfolios based on takeover probability



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

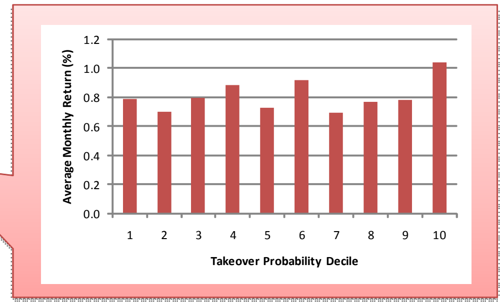
The net result is that for quant applications we actually prefer a more diversified portfolio, which seems to be commensurate with better average returns, even though we are sacrificing some hit rate to do so. The simple "buy the top decile" strategy seems to fit in well with this goal, so rather than over-complicate things by trying to optimize this, we just use this simple strategy going forward. In contrast, for fundamental investors who are purely interested in finding likely takeover targets, we recommend a more concentrated portfolio to maximize the hit rate (see the screen at the start of this report).

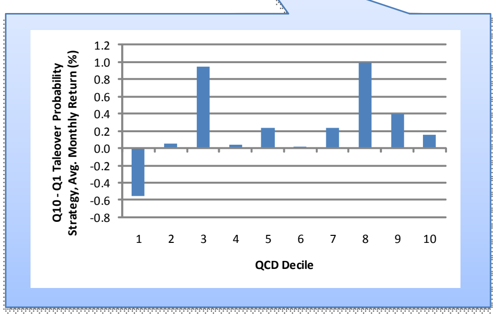
Neutralization to the rescue?

For quant investors, increasing the portfolio concentration does not seem to help. As a result, we try another idea: what if we directly control for the loser, or anti-quant exposure, that the model is taking? To get a feel for what this means, we run the simple double sort analysis depicted in Figure 30. Each month, we first sort the universe into deciles based on our QCD model, and then within each of those QCD buckets we decile stocks by takeover probability. The upper left hand table shows the average monthly forward returns for each of these portfolios.

Figure 30: Double sort analysis (sort first on QCD, then on takeover probability)

Takeover Probability Decile (higher = takeover more likely)	QCD Decile (higher = more attractive buy)										
	1	2	3	4	5	6	7	8	9	10	Avg.
1	-0.41	0.15	0.21	0.97	0.94	1.04	1.19	1.12	1.06	1.62	0.79
2	-0.27	0.28	0.55	0.53	0.58	0.84	0.66	0.85	1.36	1.65	0.70
3	-0.47	0.20	0.72	0.81	1.00	0.84	0.90	1.47	1.08	1.38	0.79
4	-0.03	0.02	0.29	0.89	1.10	0.99	1.23	1.38	1.29	1.66	0.88
5	-0.69	-0.16	0.58	0.26	0.54	1.14	1.13	1.48	1.54	1.46	0.73
6	-0.23	0.25	0.17	0.81	1.17	1.27	1.17	1.46	1.42	1.69	0.92
7	-0.55	-0.16	0.62	0.38	0.96	1.01	1.21	1.00	1.17	1.32	0.70
8	-0.15	0.20	0.68	0.60	0.74	0.75	0.99	1.26	1.49	1.11	0.77
9	-0.73	0.39	0.72	0.90	0.38	0.74	1.02	1.36	1.47	1.56	0.78
10	-0.97	0.20	1.16	1.01	1.18	1.06	1.43	2.11	1.46	1.78	1.04
10-1	-0.56	0.05	0.95	0.04	0.24	0.02	0.24	0.99	0.40	0.16	0.25





Source: Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Controlling for the negative quant exposure improves performance

The lower chart (highlighted in blue) shows the performance of a simple strategy that goes long high takeover probability (decile 10) and short low takeover probability (decile 1), *within* each of the 10 QCD deciles. As shown in the chart, once we do this the takeover probability strategy actually generates positive returns in nine out of 10 cases. Or, put another way, once we control for differences in QCD score, the takeover probability model does reasonably well.

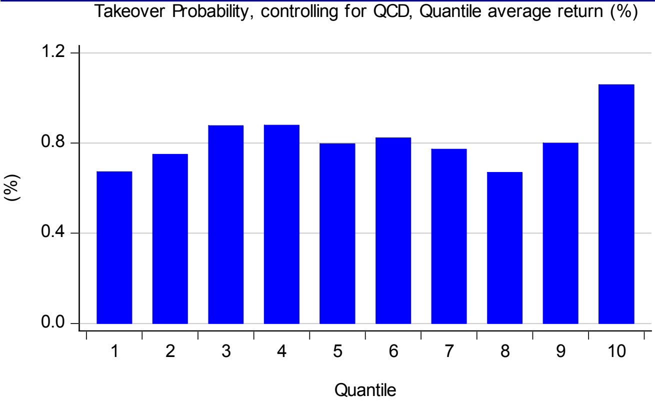
The red chart shows the average performance across each row. This is effectively the performance of each takeover probability decile portfolio, after controlling for the disparities in QCD ranking. The promising feature of the chart is that now the decile 10 portfolio actually shows some outperformance relative to rest of the decile portfolios.

A better way: Regression

We prefer to use a cross-sectional regression to strip out the anti-quant exposure

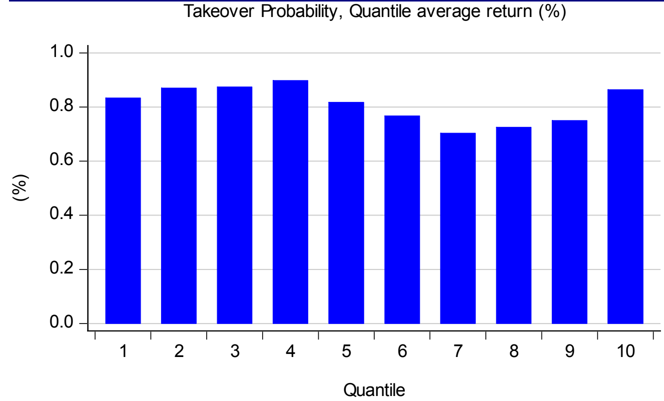
Instead of arbitrarily controlling for the QCD exposure using deciles, an arguably cleaner way to do this neutralization is to use a cross-sectional regression. At the end of each month, we simply take the takeover probability forecast by our model, and regress it onto our QCD model score. The residual from this regression then becomes our new factor, which we call the adjusted takeover probability. In Figure 31 we show the average decile portfolio returns, after controlling for the QCD exposure. For comparison, the same chart using the raw takeover probability is shown in Figure 32. The results are quite promising, and reconcile with what we saw in the double sort analysis. After stripping out the negative exposure to our QCD model, the highest takeover probability portfolio does outperform the rest of the deciles over time.

Figure 31: Average monthly decile returns, after controlling for QCD score



Source: Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

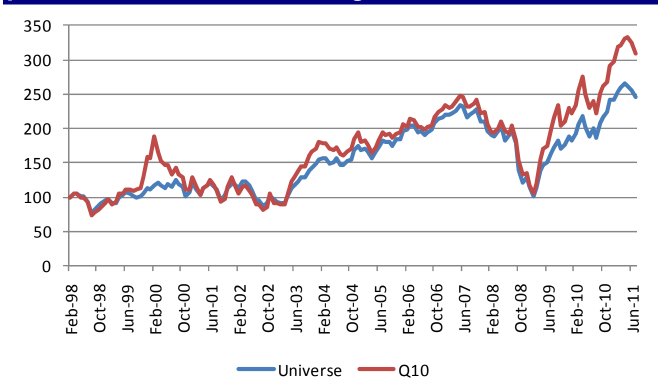
Figure 32: Average monthly decile returns to portfolios formed on takeover probability



Source: Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

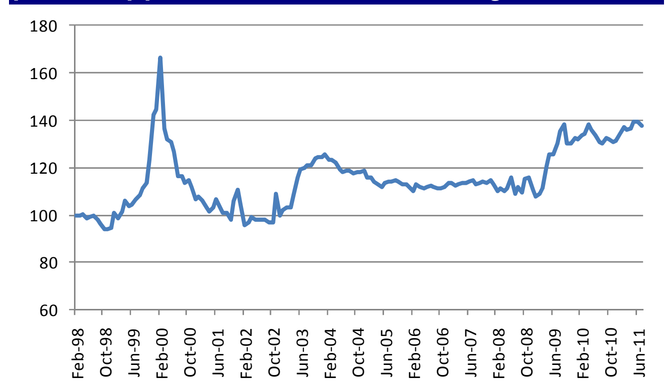
Furthermore, if we plot the cumulative performance (Figure 33) and relative cumulative performance (Figure 34) the results are better. Instead of underperformance we get a little outperformance, albeit still not spectacular. The relative performance chart shows that most of the outperformance comes from two periods that correspond to the ramp up in M&A activity at the start of the 2003-2007 bull market and coming out of the credit crisis.

Figure 33: Performance of highest takeover probability portfolio (Q10) after controlling for QCD



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 34: Relative performance of highest takeover probability portfolio (Q10) after controlling for QCD



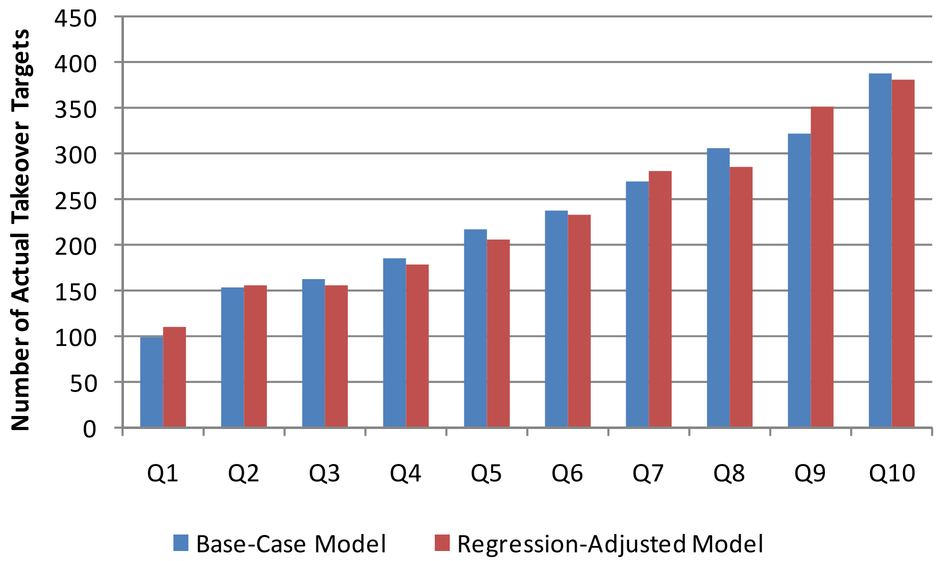
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The fact the performance comes in waves is not surprising. Clearly, if there are no takeovers happening, then there will be no large positive returns to offset all the stocks that look like they might be targets never actually get taken over. This makes the M&A prediction model a much more cyclical proposition compared to many traditional quant factors.

Using the adjusted takeover probability does not adversely impact the hit rate

As a final check of our adjustment methodology, we re-examine the hit rates from the start of this section. Figure 35 shows the number of actual M&A targets captured by each decile, using both the unadjusted and adjusted model. We find that there is very little difference between the two. In other words, it does appear that we can strip out the negative quant tilt from our model forecasts, without losing the attractive hit rate of the model.

Figure 35: Number of actual takeover targets captured, by forecast decile



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We believe removing the negative quant exposure is a worthwhile exercise

Overall our results suggest that adjusting the takeover probability to strip out the problematic negative quant exposure is a worthwhile exercise. In our backtests, using this methodology allows us to create a takeover target screen that has a relatively high hit rate, without taking on the full tilt towards loser stocks that the unadjusted screen entails. At the same time, the model is certainly not a magic bullet – it works well at points in the M&A cycle, but is not as consistent over time as some of the other quant alpha factors.

In the next section, we drill down into some of the more subtle aspects of the model.

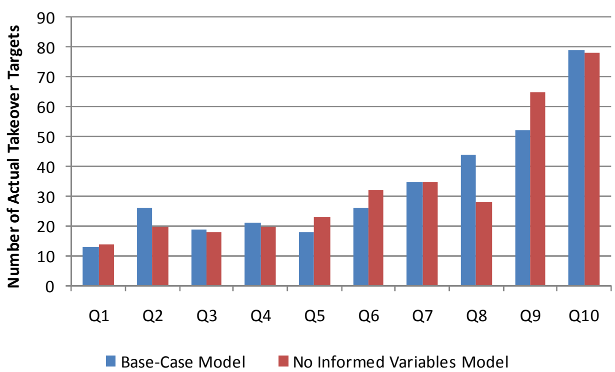
Digging deeper

New data sources: Buzzworthy, but are they worth it?

We measure the incremental value-add from using the "unique" variables

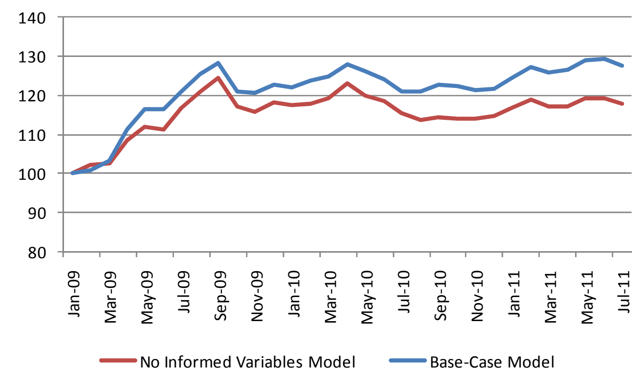
One interesting question, which we have glossed over up until now, is whether the unique, "informed trading" variables that we included are actually worthwhile. High frequency data, options data, and news sentiment data are less commonly used, harder to work with, and more expensive than the more traditional fundamental and pricing datasets that quants work with. So it is important to weigh the worth of these metrics against the incremental performance they add. To test this, we construct a second version of the model where we remove the unique variables from the pool of available explanatory variables. Figure 36 compares the hit rates of the two models, and Figure 37 tracks the cumulative performance of the highest takeover probability decile. Note that all comparisons are made only over the 2009-present period, the reason being this is the time period for which the model starts to use the informed variables.

Figure 36: Number of actual takeover targets captured, by forecast decile, with and without informed variables (2009 – present)



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 37: Performance of regression-adjusted takeover probability Q10, with and without informed variables (2009 – present)

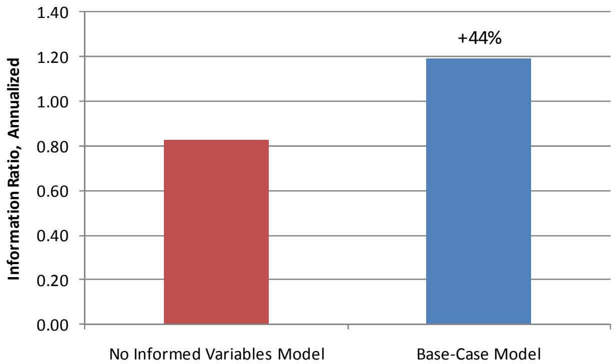


Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

In terms of the total number of M&A targets captured, the two models are roughly in line, but in terms of the cumulative performance the model that includes the informed trading variables outperforms.

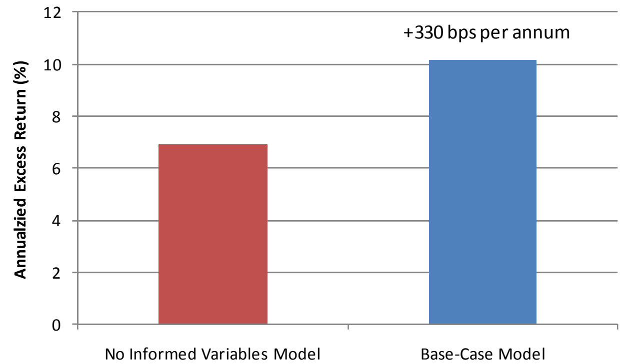
If we look in terms of risk-adjusted returns, we see the same story. Figure 38 shows the annualized information ratio for the decile 10 portfolio from both models; including the informed trading variables leads to significant gains. From an excess return perspective, over the backtest period the model with the informed trading variables outperforms the benchmark by around 10%, whereas the model with only traditional variables outperforms by only 7%.

Figure 38: Information ratio from Q10 portfolio, with and without informed variables (2009 – present)



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 39: Annualized excess returns from Q10 portfolio, with and without informed variables (2009 – present)



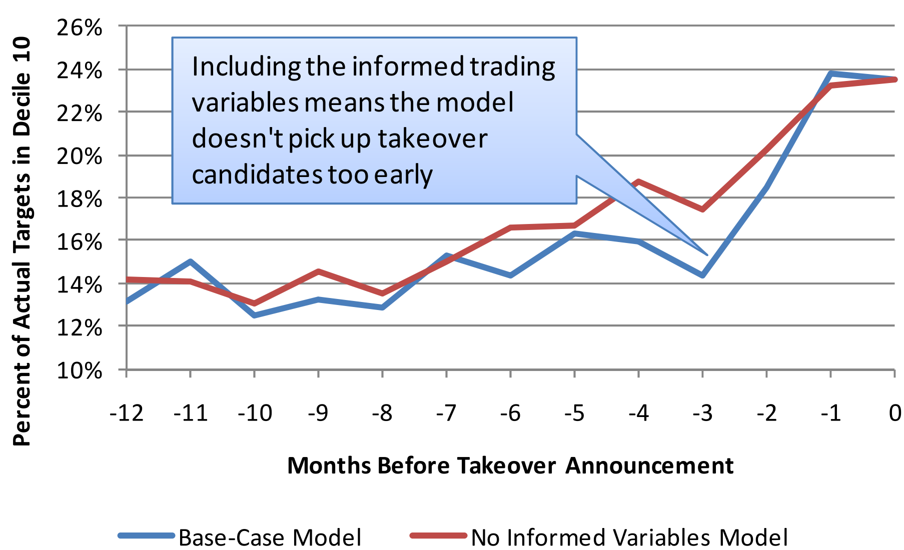
Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Where does this performance boost come from? Our hypothesis is that the informed trading variables help us in timing when a takeover is most likely to occur. In the long-term, there is little doubt that fundamental drivers like size and valuation are important. But in the short-term, the first signs that a stock is "in play" may well be detected in the options market or in high frequency trading. Therefore, our conjecture is that the high frequency variables help us avoid some of the drag associated with getting into loser stocks too early.

There is some evidence that using "informed" variables improves trade timing ability

Can we prove this? Figure 40 offers some tantalizing hints that we may be on the right track. The chart shows the percent of stocks that eventually get taken over that are in the top decile portfolio in the period 12 months before the actual announcement. Ideally, we want a model that puts us into the takeover target quite close to the actual announcement date, so that we can avoid holding the stock too long. There is some evidence that the informed trading variables help us do this.

Figure 40: Percent of actual takeover targets that models placed in Decile 10, as a function of time to announcement (2009 - present)



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

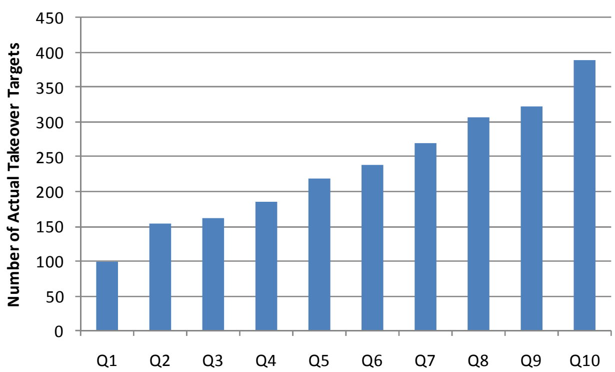
If we think back to our model estimation, we found that stocks that get taken over tend to outperform one and three months before the announcement, probably because of information leakage. It may just be a coincidence, but it does appear from the chart that this is also roughly when the model with informed variables starts putting us into stocks that will go on to become takeover targets.

Does size matter?

Our model actually works better for the S&P 500 than the Russell 3000

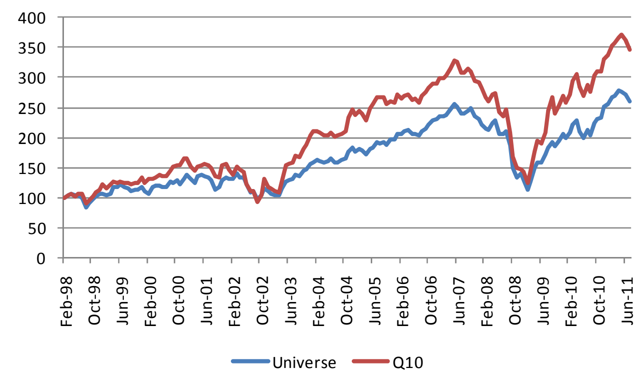
So far all our analysis has been conducted on the Russell 3000 universe. As a robustness check we repeat our key results for the S&P 500 universe. Interestingly, the model actually performs better for large caps than for the extended universe. The hit rate is still monotonic (Figure 41), and more importantly the performance of the highest takeover probability portfolio (using our QCD adjustment) is favorable relative to the benchmark (Figure 42).

Figure 41: Number of actual takeover targets, by forecast decile, S&P 500 universe



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 42: Performance of highest adjusted takeover probability (Q10) stocks versus universe, S&P 500 universe



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Case study 1: Real-world S&P 500 portfolio

In a real-world simulation our model adds value, even after costs

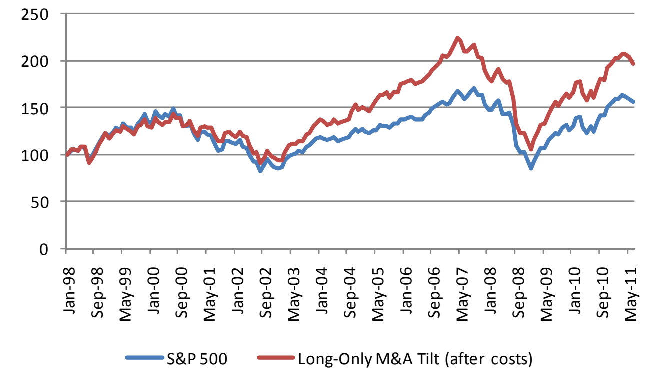
Another important robustness check is to factor in real-world constraints like transaction costs. To this end we run a realistic portfolio simulation, where we build an optimized, long-only S&P 500 portfolio that tilts towards stocks with a higher adjusted takeover probability. The portfolio is rebalanced monthly, and aims for a tracking error of 3%. Turnover is constrained to 20% two-way per month, and the portfolio is constrained to be beta and sector neutral relative to the S&P 500 benchmark. For the optimization we use the Axioma portfolio optimizer in conjunction with the Axioma medium-horizon U.S. fundamental risk model. All results reported below are after transaction costs (assumed to be 40bps two-way).

Figure 43: After-cost performance statistics for M&A Tilt portfolio

Excess Return (annualized)	1.6%
Tracking Error (annualized)	3.6%
Information Ratio (after costs)	**0.45**
Max. Monthly Drawdown vs Benchmark	-2.2%

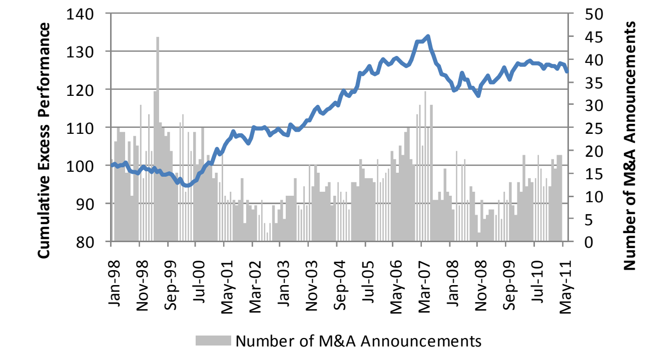
Source: Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 44: After-cost performance of M&A Tilt portfolio and S&P 500 benchmark



Source: Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 45: After-cost relative performance of M&A Tilt portfolio versus S&P 500 benchmark



Source: Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

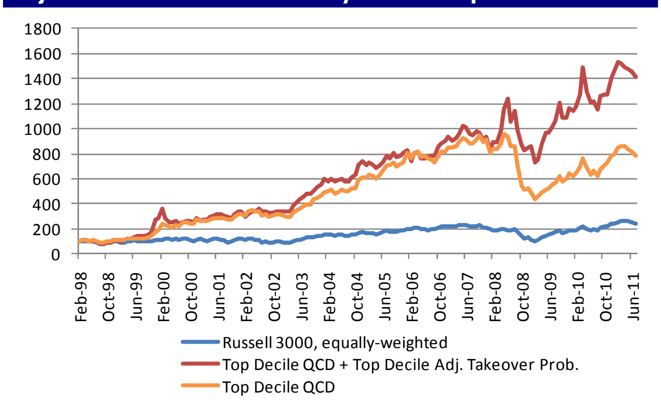
Over the backtest period, the portfolio generates an information ratio of 0.45 after costs. Figure 45 shows the cumulative performance of the portfolio relative to the benchmark, again after costs. Unlike the naïve equally weighted strategy than went long the top decile, the fully optimized strategy does deliver more consistent returns. However, there are still periods of major drawdowns, particularly through the financial crisis. Again, this is not surprising. A strategy of buying stocks that look like they might get taken over (i.e. loser stocks) is always going to underperform when there are no actual takeover announcements to offset this drag.

Case Study 2: Concentrated quant + takeover portfolio

We can also add value by combining a quant model with the adjusted takeover model

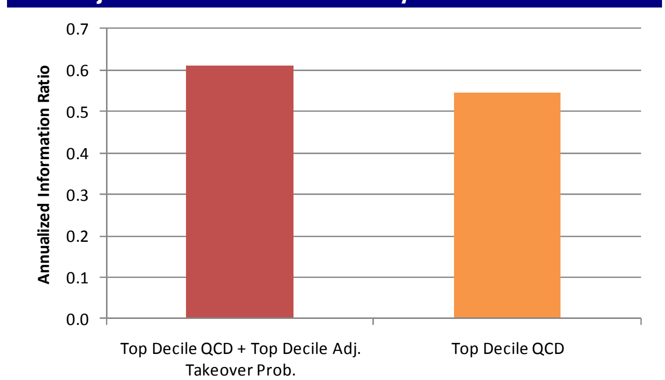
For a second example of how we might use our takeover model, we swing to the other end of the risk spectrum. Suppose we construct a concentrated portfolio that consists only of stocks that fall into the top decile of our adjusted takeover model *and* the top decile of our QCD alpha model? Figure 46 shows the cumulative performance of this portfolio (the red line), compared to (1) the Russell 3000 universe, and (2) the top decile QCD portfolio on its own.

Figure 46: Performance of concentrated QCD Decile 10 + Adjusted Takeover Probability Decile 10 portfolio



Source: Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 47: Information ratio for concentrated QCD Decile 10 + Adjusted Takeover Probability Decile 10



Source: Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Since the end of the last bull market the concentrated portfolio has done quite a bit better than the QCD model on its own, and the Russell 3000 index. Of course, the concentrated portfolio also has higher risk, so it is important to consider risk-adjusted returns, which we show in Figure 51. The chart shows the annualized information ratio of both portfolios relative to the universe. Even on a risk-adjusted basis, adding the takeover model adds value.

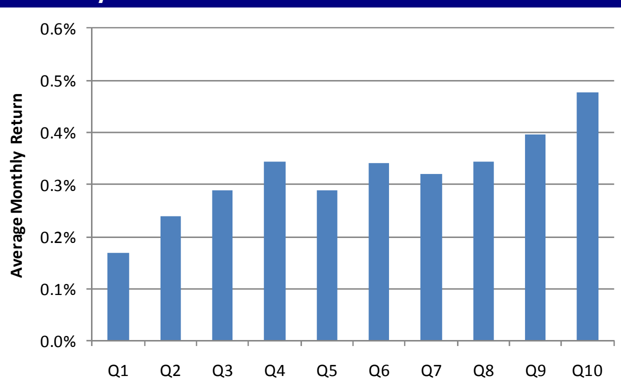
Case Study 3: Building better portfolios

In our *Portfolios Under Construction* research series, we have spent considerable time searching for ways to improve the way we convert a quant factor into a tradable portfolio. Can some of these techniques help us better harvest the alpha in this factor?

We test two potentially better ways to construct the factor portfolio:

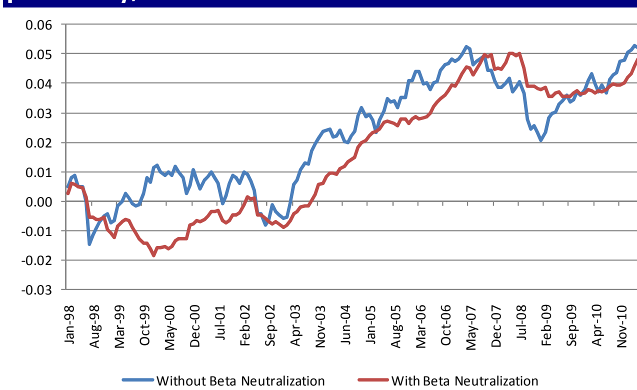
- First, we build simple decile portfolios as before, except instead of equally weighting within each decile, we weight in proportion to each stock's takeover probability (Figure 48).[8] Essentially this ensures that the capital allocation to each stock is more commensurate to the takeover probability. From the chart this technique does a good job of ensuring the desirable monotonic pattern in the decile returns. Note that here we have used the *unadjusted* takeover probability, so this technique offers a potential alternative to the cross-sectional regression that we used to adjusted the factor scores in order to get a similarly monotonic return profile.
- Second, we experiment with using the fully-fledged neutralization technique that we described in Alvarez et al. [2010] (Figure 49). Instead of using a simple cross-sectional OLS regression against the QCD score, we use a weighted regression against beta. The weighted regression uses the asset-by-asset covariance matrix from our risk model to better account for correlation and volatility. The chart shows the cumulative performance of a factor-mimicking portfolio constructed using the unadjusted takeover probability signal and the signal neutralized to beta. The neutralized version does appear to survive the drawdown in the financial crisis better, which is understandable since the neutralization technique is designed to strip out the factor's inherent exposure to risk.

Figure 48: Portfolio weights proportional to takeover probability



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 49: Portfolio weights proportional to takeover probability, with and without beta neutralization



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Further research: Optionality?

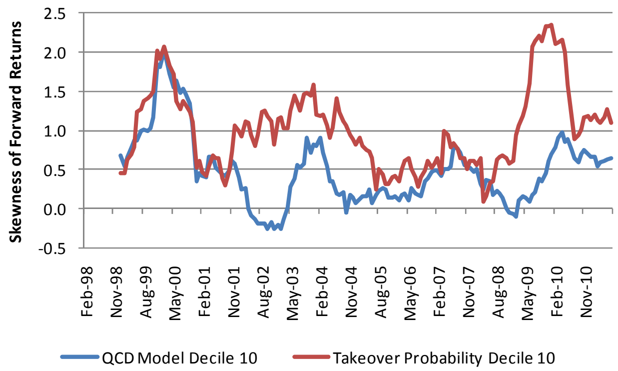
In the future we want to test whether we can use options strategies to harness the positive skewness in our strategy

One final point that we think is worthy of future research is the idea of harvesting some of the alpha from this strategy through an options strategy. At the risk of laboring the point, the biggest problem with an M&A forecasting model is that there are far more false positives than there are actual takeovers. But suppose we bought call options over the stocks in the top decile? Such a strategy might allow us to tilt the performance seesaw in our favor. Because the option premium that we would pay in buying the options would be low relative to the upside from the stocks that do get taken over, we might be able to capture more of the upside at a lower cost.

[8] For more details on this methodology, see page 17-18 of: Alvarez, M., Y. Luo, R. Cahan, J. Jussa, and Z. Chen, 2011, "Signal Processing: Reviving momentum – Mission impossible?", *Deutsche Bank Quantitative Strategy*, 6 July 2011

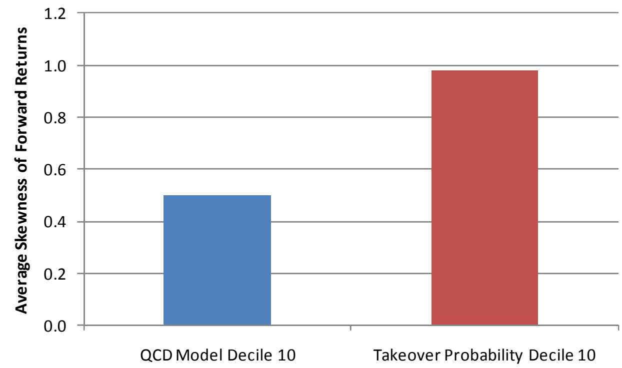
Figure 50 shows why. Over time, the top decile portfolio for the adjusted takeover model has much higher cross-sectional skewness in returns compared to a normal quant model.

Figure 50: Skewness of cross-sectional return distribution (12m rolling average)



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

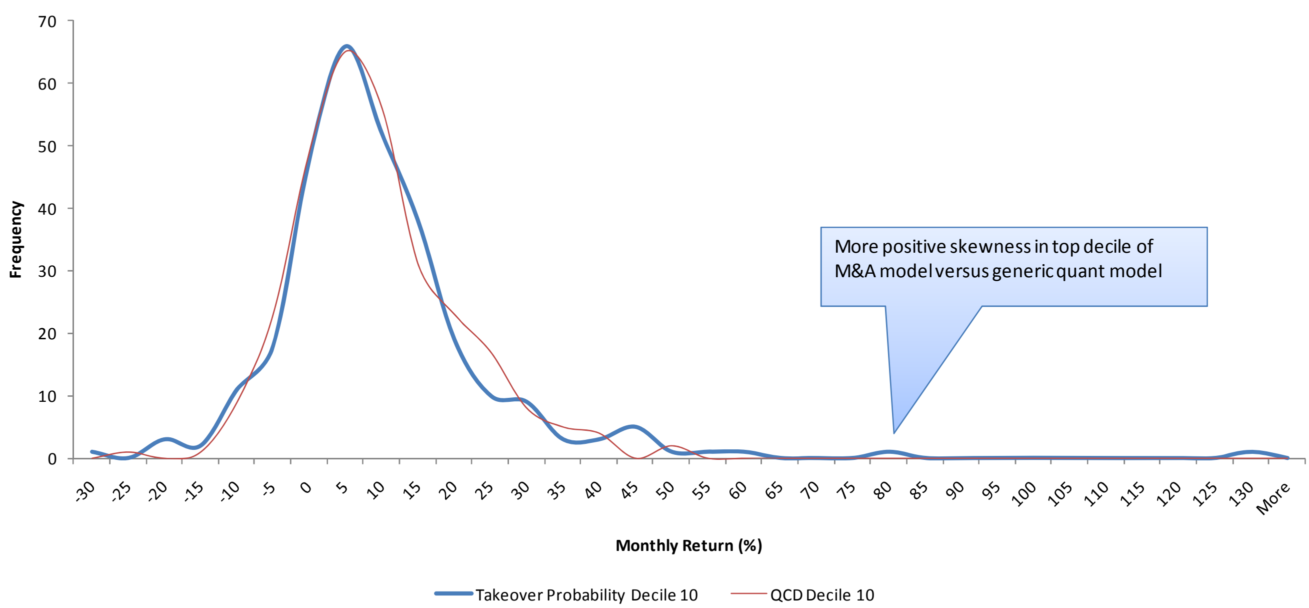
Figure 51: Long-term average skewness of cross-sectional return distribution



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 52 shows a snapshot of the two cross-sectional return distributions at one point in time. As expected, the takeover probability model has more large positive outliers than the normal quant model.

Figure 52: Snapshot of cross-sectional return distribution, as at 31 January 2011



Source: Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The idea of harvesting some of this skewness through an options strategy is something we plan to explore in future research.

References

Alvarez, M., Y. Luo, R. Cahan, and J. Jussa, 2010, "Portfolios Under Construction: Volatility = 1/N", *Deutsche Bank Quantitative Strategy*, 16 June 2010

Alvarez, M., Y. Luo, R. Cahan, J. Jussa, and Z. Chen, 2011, "Signal Processing: Reviving momentum – Mission impossible?", *Deutsche Bank Quantitative Strategy*, 6 July 2011

Brar, G., D. Giamouridis, and M. Liodakis, 2009, "Predicting European takeover targets", *European Financial Management*, Volume 15, Number 2

Cahan, R., Y. Luo, M. Alvarez, and J. Jussa, 2010a, "Signal Processing: The options issue", *Deutsche Bank Quantitative Strategy*, 12 May 2010

Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010b, "Signal Processing: Beyond the headlines", *Deutsche Bank Quantitative Strategy*, 19 July 2010

Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010c, "Signal Processing: Frequency arbitrage", *Deutsche Bank Quantitative Strategy*, 11 November 2010

Chadha, B., P. Thatte, and K. Parker, 2009, "M&A: Buy acquisition targets", *Deutsche Bank US Equity Strategy*, 20 October 2009

Luo, Y., R. Cahan, J. Jussa, and M. Alvarez, 2010a, "QCD Model: DB Quant Handbook", *Deutsche Bank Quantitative Strategy*, 22 July 2010

Luo, Y., R. Cahan, J. Jussa, and M. Alvarez, 2010b, "Signal Processing: Style rotation", *Deutsche Bank Quantitative Strategy*, 7 September 2010

Palepu, K., 1986, "Predicting takeover targets: A methodological and empirical analysis", *Journal of Accounting and Economics*, Volume 8

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Appendix 1

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