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BEAM (Bonds in Equity Asset Momentum)

Equity Momentum Strategies Based on Credit Signals: Scope, Frequency and Aggregation

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- **Several years ago we started to examine whether systematic equity strategies can benefit from incorporating cross-market information from credit markets. In particular, can corporate bonds return dynamics be used to improve the construction of equity momentum portfolios?**
- **We compared the performance dynamics of the standard momentum portfolio based on ranking past equity returns with a second momentum portfolio (BEAM) that instead ranked stocks by the past excess returns of bonds issued by the same set of firms. Hence, both momentum portfolios shared the same initial universe of firms and included only equities but differed in the source of the information used for ranking.**
- **Employing corporate bonds return dynamics resulted in consistently higher performance and lower volatility, especially in periods of market reversals in which the standard momentum portfolio was found to perform poorly. As a result, the BEAM portfolio generated an information ratio that was three to four times that of the standard momentum portfolio.**
- **This report provides updated performance figures for the BEAM strategy. BEAM has continued to deliver strong positive returns that are remarkably consistent with the original study in 2014.**
- **BEAM's performance has been stable over time, with positive returns every year since 1999, across market states, and all industries.**
- **BEAM signal is valuable both in isolation and when combined with other strategies. Using BEAM strategy generates significant alpha after controlling for commonly used asset pricing factors, and when combined with momentum it provides considerable diversification benefits.**
- **BEAM's performance remained strong after accounting for trading costs, including price impact, shorting costs, and execution lags.**
- **Since 2014, we have continued to carry out research on the information value of bond signals for equity investors. We found that BEAM is robust across regions (in U.S. and European markets) and frequencies (daily and monthly frequency), and different levels of signal aggregation (individual stock- and sector-level). These new results provide compelling out-of-sample tests of the original U.S. BEAM results, and confirm the value of using credit signals in equity portfolios.**

Equity Momentum Strategies Based on Credit Signals

About four years ago, Ben Dor and Xu (*2014*) introduced the idea of employing credit signals to invest in equities. They showed that a portfolio constructed by ranking equities based on the aggregate returns of their bonds, in which the 'long' and 'short' legs of the portfolio are populated by the corresponding stocks, generates higher future equity returns. Bond-ranked portfolios, henceforth defined as BEAM (Bonds in Equity Asset Momentum), produces an information ratio that is about ten times that of the standard equity momentum portfolio (1.16 versus 0.13), with both higher average returns and lower monthly volatility.

The idea of using price information from other markets, in particular the corporate bond market, is intuitively appealing. For instance, the Merton (1974) model predicts the co-movement of corporate bonds and equities as the value of the firm drives both the price of equity and debt of the issuing entity. Using credit signals for systematic equity strategies is, however, easier said than done. Although the U.S. corporate bond market is enormous, with outstanding principal larger than $9trn in Q1 2018 (source: *SIFMA*), corporate bonds trade over-the-counter, trade less frequently and are less liquid than equities. For all these reasons, one challenge in using credit signals in systematic equity strategies is the lack of a high-quality, easily accessible and comprehensive corporate bond pricing dataset, which comprises both prices and analytics, unlike those datasets available for equities. The most significant bottleneck to using bond prices for equity investing is, however, the availability of a reliable linking algorithm between bonds and stocks and cross asset class expertise. Indeed, to incorporate bond-level information in the construction of equity portfolios, we need to be able to observe a firm's capital structure, and specifically to have a reliable linking table between the bond identifier (at the security level) and its parent company, as these data are not commercially available. Furthermore, to implement BEAM an additional key input beyond those usually required to build successful style portfolios (according to Israel, Jiang and Ross, 2017, called "craftsmanship" alpha) is essential − namely cross asset class expertise needed for the signal construction.

Building on the seminal work of Ben Dor and Xu (2014), this report provides updated performance figures for the BEAM strategy. The exercise is informative as the out-of-sample performance of a model is often viewed as the 'gold standard' of evaluation. Since the publication of the report, we have now more than four years of live data to assess BEAM performance. Moreover, we can examine BEAM performance relative to other equity strategies by comparing BEAM performance with that of the most commonly used asset pricing portfolios (Fama and French, 2015).

In the second part of the paper, we look at the consistency of BEAM performance along several dimensions, including across industries, over time and by market states. In particular, we investigate whether BEAM represents an industry bet, and to what extent the performance of BEAM is driven by sector allocation. We also examine the consistency of BEAM returns, both over calendar time (i.e., years or months) and across different economic states.

A central investing tenet is that the value added of a signal should not be considered in isolation, but rather in a portfolio setting when combined with other signals. In this respect, understanding how BEAM returns relate to other standard risk factors is as important as assessing the BEAM performance as a stand-alone strategy. We use both parametric and non-parametric methods to shed light on the diversification benefits from combining BEAM with other strategies. By doing so, we address a number of inquiries we received from investors following the publication of the original study, such as what is the relationship between BEAM and momentum? Is there any value of combining BEAM and momentum signals together? Are BEAM returns explained by exposures to commonly used asset pricing factors? To assess the potential value of BEAM to real investors we also consider the incremental performance that could be achieved in an ex-post mean-variance efficient portfolio by including BEAM as an investable asset.

Our analysis has mostly focused on the expected gross returns of the BEAM strategy. Whether investors can benefit from the BEAM signal in practice, however, critically depends on the net of transaction cost returns. Hence, we explore whether the BEAM strategy is implementable and sizeable, or whether it faces significant practical impediments that prevent investors from profiting from it. The robustness of BEAM performance to trading costs and capacity limits is evaluated by taking into consideration three implementation aspects: day and time of trade execution, price impact and shorting costs.

A key finding is that the BEAM strategy has continued to deliver strong positive returns since the publication of the original study in 2014. In the out-of-sample period average returns are 18.5% and its information ratio is 0.85 compared with 17.4% and 1.16 in the in-sample period. Moreover, BEAM performance is better (i.e., higher average returns and lower volatility and tail risk measures) than that of the most commonly used asset pricing portfolios. One potential reason why in the post-2014 period BEAM performance has remained similar to that of the in-sample period is that BEAM is hard to replicate, as it requires access to an exhaustive fixed income dataset, a real-time mapping algorithm between bonds and stocks and cross asset expertise.

We document that BEAM performance has been consistent along several dimensions. In particular, BEAM performance is not driven by industry exposures, and has been positive across all industries. An industry-neutral BEAM portfolio generates similar returns compared with a BEAM portfolio in which stocks are ranked across the overall universe, but displays lower volatility. Furthermore, BEAM's performance has been stable over time, with positive returns every year since 1999, and by market states.

The results indicate that the information contained in bond prices is useful in constructing equity momentum portfolios. Whether investors can benefit from the BEAM methodology, however, is another matter. We study several aspects related to the implementation of the BEAM strategy in practice. We show that the BEAM signal is valuable not only in isolation, but also in a portfolio setting when combined with other strategies. Using parametric methods, we show that BEAM is not spanned by exposures to commonly used asset pricing factors. Furthermore, BEAM generates significant alpha relative to those factors. Hence, an investor already trading the Fama and French factors could realize significant gains in an ex-post mean variance efficient portfolio setting by starting to trade BEAM. Using non-parametric methods, we find that there is considerable diversification benefit from combining momentum and BEAM strategies, despite BEAM signals being only available for a subset of equities comprising Russell 1000 universe.

We show that BEAM performance is robust to trading costs and capacity limits. BEAM generates an information ratio of about 1 after taking into account price impact, shorting costs and potential execution lags both in the original sample and in the post-2014 period. Furthermore, since companies that issue corporate bonds are to a large extent large-cap, BEAM strategy is easier to implement compared to other equity strategies. In this respect, most stock anomalies (i.e., patterns in average stock returns that are not explained by the CAPM) are concentrated in micro- and small-caps, which represent only 3% of the total market capitalization of the NYSE-Amex-NASDAQ universe, but account for 60% of the number of stocks (see, e.g., Hou, Xue and Zhang, 2017, for detailed evidence).

Since 2014, we have continued to carry out research on the information value of bond signals for equity investors. We have extended BEAM to European markets and at higher frequency, i.e., by using daily corporate bond prices in high-frequency equity momentum strategies (Daily-BEAM or in short D-BEAM). We have also looked at BEAM performance at a different level of signal aggregation, and whether the BEAM signal can be helpful for sector timing. Ben Dor, Guan and Zeng (*2018*) document that similar to the U.S. incorporating information from bond prices enhances the traditional equity momentum strategy also in Europe. The monthly European BEAM portfolio delivers an annualized information ratio of 0.74 for the period between 2003 and 2017, whereas the traditional equity momentum portfolio generates an information ratio of 0.26 over the same period. Ben Dor, Guan and Rosa (*2018*) show that the use of daily bond signals delivered an annual average return of 18% and an information ratio of 1.8 starting in 2001. Moreover, they continued to generate momentum patterns, while equity returns exhibited mean-reversion at higher frequency. The similarity of performance dynamics in those markets demonstrates that BEAM is robust across regions and frequencies, and different level of signal aggregation.

The results of BEAM across geographies, at high frequency and at a different level of aggregation can be interpreted as providing compelling out-of-sample tests of the original U.S. BEAM finding, and confirm the value of using credit signals in equity portfolios. More generally, from an investor's standpoint, because the BEAM signal works internationally and at high-frequency, the breadth of the strategy is broader than originally thought, thus enhancing the profit opportunities.

The remainder of this report is organized as follows. The next section provides an update of the performance of BEAM since its discovery in 2014. Then, we look at the consistency of BEAM performance along a number of dimensions, including across industries, over time and by market states. We proceed by examining some practical implementation issues, such as combining BEAM and equity momentum signals, combining portfolios, and evaluating the impact of transaction costs on BEAM performance. Since 2014, we have expanded the BEAM coverage along three dimensions: BEAM signals for European markets, at daily frequency, and for sector timing. We conclude with a discussion of some additional applications of the unique cross-asset bond-equity dataset documented in this analysis.

The Performance of BEAM Since Its Discovery

We begin with an update on the performance of BEAM since the publication of the original study of Ben Dor and Xu (*2014*), i.e., from January 2014 to present. Figure 1 shows various performance measures for the BEAM and momentum strategies. To facilitate the comparison, the table displays the same statistics for the period January 1994 to December 2013 in the left panels, for the period January 2014 to August 2018 in the middle panels, and for the period January 1994 to December 2013 excluding market crashes in the left panels. Portfolios are rebalanced monthly. Returns are equally weighted and ignore transaction costs.[1] All strategies are formed on univariate sorts, and are based on portfolio deciles. All portfolios are based on the BEAM universe, i.e., the universe of equities with outstanding Bloomberg-Barclays index bonds.

In the period 1994-2013, BEAM has an average annualized return of 17%, an annualized volatility of 15%, and an annualized information ratio of 1.16. The novel aspect of the Figure 1 is the BEAM performance in the post-sample (i.e., 2014-2018) period, both in absolute and relative to existing portfolios. The key finding is that since the publication of the paper the BEAM performance has remained similar to that of the in-sample period, with an annualized average return of 18%. BEAM volatility has been somewhat higher in the post-sample period compared with the 1994-2013 period, at 22% and 15%, respectively. The increase in volatility in turn generates a lower information ratio (i.e., 0.85) in the post-sample period.

[1] We leave the transaction cost adjustment to the implementation stage, as different signals may be combined in the portfolio construction process.

The information ratio does not do justice to BEAM performance as the information ratio does not differentiate between good and bad volatility. In other words, volatility measures dispersion of returns around their average value. As such, both returns above or below the mean contribute to increase the level of volatility. From an investor's standpoint, returns above the mean represent, however, a good type of risk. The Sortino ratio modifies the information ratio by penalizing only those returns falling below a certain threshold (known as minimum acceptable return). According to the Sortino ratio, BEAM performance has remained remarkably stable, at 1.91 in the post-sample period compared with 1.97 in the original sample. Hence, the increase in volatility is mostly associated to an increase in upside deviation, rather than to an increase in the overall risk profile of the BEAM strategy. Additional measures of downside risk, such as minimum monthly return and maximum drawdown, have also remained stable in the two sample periods.

The finding that BEAM performance remained strong is in stark contrast to the results reported in Chen and Velikov (2018). They showed that trading costs and post-publication decay account for the great majority of stock return anomalies. One potential reason why BEAM profitability has not been traded away is that its construction relies on data that are not commercially available, such as an exhaustive fixed income dataset (which comprises both prices and analytics) and especially a robust real-time mapping algorithm between each firm's bond and equity data.[2]

To put BEAM performance figures in context, Figure 1 reports the performance of equity momentum, a well-established empirical fact where, on average, stocks with strong recent performance relative to other stocks in the cross section of returns tend to outperform in the future. As standard in the academic literature, we consider the 12-1 ranking window, namely we measure the total return of a stock over the past 12 months, skipping the most recent month. In the period 1994-2013, the annualized average return for the momentum strategy was about 4%, whereas for the post-sample period is about 17%. The volatility has remained roughly constant at 30%. Thus, the information ratio in the post-sample period is about 0.6. As we will discuss more in detail below, the improvement in the momentum performance can be ascribed to the absence of market crashes, i.e., infrequent, persistent and large strings of negative returns, in the post-2014 sample period. Indeed, the left panel of Figure 1 reports the performance of equity momentum in the original sample, excluding the years 2002-2003 and 2008-2009, which coincide with periods of rapid market reversals from severe troughs. The most interesting aspect is, however, the stability of BEAM performance in good and bad times. Despite excluding four years, BEAM's information ratio, at 1.13, is barely affected. This finding indicates that BEAM continues to generate strong performance also in the 2002-03 and 2008-09 years. During those years, BEAM information ratio is actually 1.51, hence even higher than its full sample value.

BEAM outperformed equity momentum not only in terms of average returns and information ratio, but also in terms of realized downside risk. Furthermore, BEAM's outperformance is consistent both in-sample and out-of-sample. For instance, in the post-2014 period (i.e., a particularly favorable period for momentum given the absence of market crashes), BEAM minimum return was -10% and its maximum drawdown was -23% compared with -28% and -39%, respectively, for equity momentum.

[2] Israel, Jiang and Ross (2017) emphasize the importance of "craftmanship" alpha that is required to build effective style portfolios. For implementing BEAM is essential an additional key input beyond the know-how needed to create successful factor portfolios, namely the cross asset class expertise needed for the signal construction.

FIGURE 1

BEAM Performance Update

Sample:	Ben Dor and Xu (2014; Figure 7)		Out-of-sample		Original sample excl. crashes	
	1994-2013		2014-2018		1994-2013 excl. 2002-3 and 2008-9	
	BEAM	Momentum	BEAM	Momentum	BEAM	Momentum
Avg Ret (%/year)	17.38	3.70	18.46	16.57	15.07	12.21
Std Dev (%/year)	14.97	29.35	21.69	29.74	13.36	20.91
Inf Ratio (ann.)	1.16	0.13	0.85	0.56	1.13	0.58
Sortino Ratio (ann.)	1.97	0.16	1.91	0.87	1.77	0.82
Min (%/month)	-19.28	-57.19	-9.59	-28.21	-19.28	-40.48
Max Drawdown (%)	-21.24	-87.79	-22.88	-39.40	-21.24	-40.48

Note: The sample periods are January 1994 to December 2013 (left panel), January 2014 to August 2018 (middle panel), and January 1994 to December 2013, excluding 2002-2003 and 2008-2009 (right panel), respectively. BEAM and Momentum portfolios are sorted across the overall universe of equities with outstanding Bloomberg-Barclays index bonds. The minimum acceptable return for the Sortino ratio is set to zero.

Source: Compustat, Bloomberg, Barclays Research.

At this point, a natural question arises: how does BEAM performance compare with that of the standard Fama-French long-short portfolios, usually considered the standard staples of asset pricing.[3] Figure 2 reports the information ratios for those portfolios for three sample periods: 1994-2013 (original sample; dark blue bars), 2014-2018 (out-of-sample; medium blue bars), and 1994-2013 but excluding market crashes (light blue bars). In line with BEAM construction methodology, all Fama-French strategies are formed on univariate sorts, and are based on portfolio deciles. Returns are equally-weighted, and ignore transaction costs. The first two set of bars are based on the BEAM universe, i.e., the universe of equities with outstanding Bloomberg-Barclays index bonds. The Fama-French factors are sorted across the CRSP universe, which include all stocks quoted in NYSE, NYSE American, NASDAQ stock exchanges.

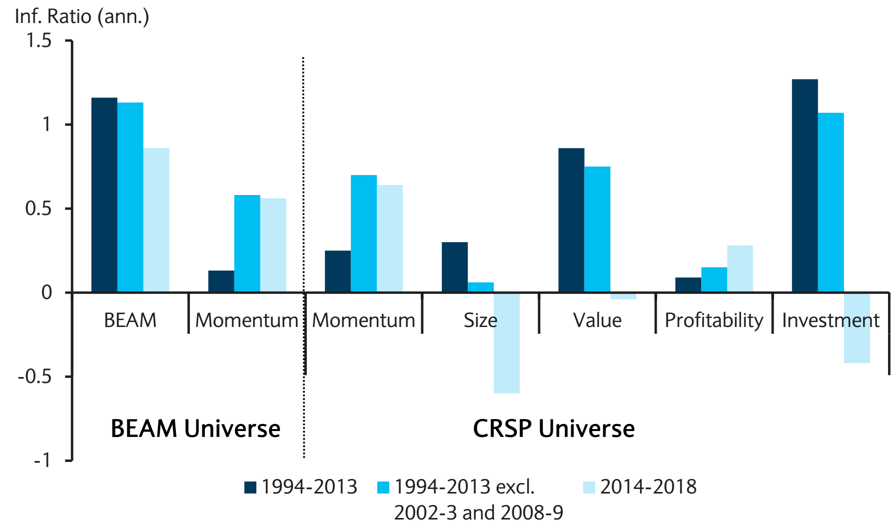
The key finding of Figure 2 is that BEAM has consistently displayed the highest information ratio both in-sample and out-of-sample compared with all other strategies. Put differently, BEAM information ratio is *large* and *stable* across different sample periods. The Investment factor is the only factor that displays an information ratio higher than that of BEAM, but only the 1994-2013 period. The Investment factor was, however, published in 2015 (Fama and French, 2015), and was not yet widely used by practitioners in 1994. Even more importantly, the Investment factor performance has become negative since the publication of the paper. Moreover, the well-established Size effect, i.e., the return premium earned by small companies compared with large companies, has become negative since 2014.

Another interesting aspect of Figure 2 is the similarity of the Momentum performance in the BEAM universe and the CRSP universe, both on average and in each sub-period. Although the construction methodology resulted in a sample that in the BEAM universe is skewed toward larger capitalization stocks (as companies with outstanding bonds included in the Bloomberg Barclays index tend to be larger), the factor performance and dynamics is not affected by the specific set of companies used in the study. An important implication of this result is that any outperformance we see in BEAM is not an artifact of the particular sample, but a consequence of the information content embedded in the bond signal.

[3] We thank Ken French for making available a rich data library containing the time-series data for various risk portfolios (*http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*), including the Fama-French three and five factor model and historical benchmark returns. These factors are described in Fama and French (1993 and 2015).

FIGURE 2

BEAM Performance Compared with Standard Risk Factors



Note: The sample periods are January 1994 to December 2013, January 1994 to December 2013 excluding 2002-2003 and 2008-2009, and January 2014 to August 2018. BEAM and Momentum portfolios are sorted across the overall universe of equities with outstanding Bloomberg-Barclays index bonds. The Fama-French factors are sorted across the CRSP universe, are based on decile portfolios. All returns are based on equally-weighted portfolios. Factor returns and definitions are available on Ken French's website.

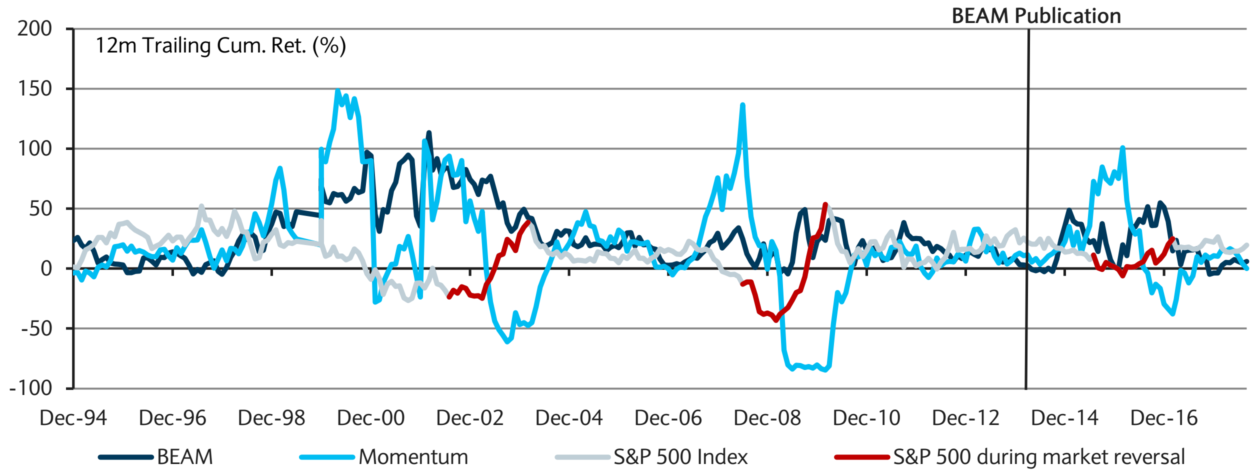
Source: Compustat, Bloomberg, Ken French Data Library, Barclays Research

So far we looked only at summary statistics. Figure 3 provides additional information about the time series properties of the performance of BEAM (dark blue line) and momentum (light blue line) by plotting the trailing 12-month cumulative returns. The gray line displays the cumulative returns of the S&P 500, and periods of market reversals are highlighted in red. The vertical line indicates when the Ben Dor and Xu (2014) report was published.

We find that BEAM trailing 12m return is positive not only on average but most of the times (e.g., about 90% of the times both in the original sample and post-publication period). Moreover, BEAM outperforms momentum in volatile periods, such as in 2003 when the U.S. stock market rebounded swiftly from a trough. The performance of momentum portfolio is not only more volatile than BEAM portfolio in the overall sample, but also it experienced a few crashes. Consistent with previous findings (see, e.g., Barroso and Santa-Clara, 2015; Daniel and Moskowitz, 2016), these momentum crashes tend to occur in panic states, namely following market declines and around market rebounds (as displayed by the red line). In the post-publication period it is reassuring to find that BEAM return dynamics during the market reversal of 2015-2016 remain consistent with earlier, in-sample, results.

FIGURE 3

Trailing 12-month Cumulative Performance of BEAM and Momentum Portfolios



Note: This figure plots the trailing 12-month cumulative returns for BEAM and Momentum (equally weighted) portfolios, and the S&P 500 index. Periods during S&P 500 market reversals are in red. The vertical dotted line indicates the date when the BEAM paper was published.
Source: Compustat, Bloomberg, Barclays Research

Consistency of BEAM Performance: Across Industries, Over Time and by Market States

Industry-Neutral BEAM

Previous research has shown that industry effects can play a key role in determining the performance of equity portfolios. For instance, Bali, Demirtas, Hovakimian and Merrick (2006) examine industry effects on stock valuation and portfolio construction, and document that industry-neutral portfolios generate significantly positive returns. Similarly, Liu, Pong, Shackleton, and Zhang (2014) show that industry-neutral portfolios generate better performance compared with those based on the full-universe for portfolios formed according to various option-implied measures. To check whether and to what extent BEAM results are driven by industry exposures, we construct industry-neutral portfolios, and compare their performance with those portfolios that do not consider industry exposure.

Figure 4 reports the performance of BEAM and momentum portfolios, where stocks are ranked across the overall universe and within industries, and the S&P 500 index as a benchmark, for the sample period from January 1999 to August 2018. By construction, the portfolios ranked across industries contain the same number of stocks as the portfolios ranked within industries, but may be substantially exposed to industry effects. We start the sample in 1999 because we need a larger sample of companies to construct meaningful industry-neutral BEAM portfolios, and ensure that each industry is well represented. As shown in Ben Dor and Xu (2014), the number of companies included in the BEAM universe in 1994 is 444 compared with 753 in 1999.

BEAM portfolio performance improves in risk-adjusted terms when implemented in its industry-neutral hedging form. Specifically, ranking within industry generates similar returns compared to ranking across industries, but displays lower volatility, hence resulting in an increase in its information ratio by about 20%. Furthermore, the construction of industry-neutral portfolios considerably improves measures of downside risk. For instance, the maximum drawdown decreases to 17% from 27% after controlling for industry exposures.

Momentum returns and information ratios are higher when stocks are ranked across the overall universe, but volatility and tail risk measures are better for industry-neutral momentum strategies. These findings indicate that momentum strategy returns had a sector allocation component.

FIGURE 4

Performance of Momentum and BEAM across vs. within Industries

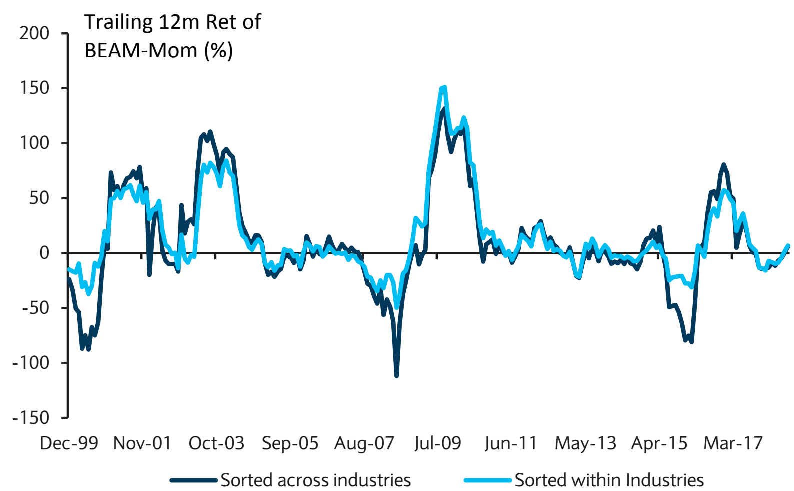
	S&P500 Index	BEAM						Momentum					
		Ranked Across Industries			Ranked Within Industries			Ranked Across Industries			Ranked Within Industries		
		L-S	L	S	L-S	L	S	L-S	L	S	L-S	L	S
Avg. Ret. (%/year)	7.32	25.93	22.46	-3.47	23.08	22.90	-0.18	14.52	16.57	2.05	8.19	15.06	6.87
Vol. (%/year)	14.33	18.93	27.02	30.89	13.92	23.95	27.46	37.10	22.03	41.07	28.00	18.48	35.64
Sharpe/Inf. Ratio (ann.)	0.36	1.37	0.75	-0.18	1.66	0.87	-0.08	0.39	0.66	0.00	0.29	0.70	0.13
Sortino Ratio (ann.)	0.52	2.74	1.35	-0.24	3.81	1.56	-0.10	0.52	0.97	0.00	0.35	1.04	0.21
Min (%/month)	-16.79	-23.39	-23.80	-31.20	-16.50	-20.57	-32.92	-63.14	-24.53	-26.52	-53.92	-21.76	-28.01
Max Drawdown (%)	-50.95	-27.48	-67.38	-91.72	-16.50	-58.91	-85.68	-89.05	-65.56	-92.77	-82.56	-56.83	-82.64

Note: The sample period is January 1999 to August 2018. This table displays summary statistics of returns for the S&P 500 index, BEAM and momentum portfolios. Stocks are ranked across the overall universe or within industries. To construct industry-neutral portfolios, fixed income industries are used for BEAM and GICS 2-digit sectors are used for momentum. BEAM is based on a 3-month ranking window and Momentum on a 12-month ranking window skipping the most recent month. The portfolios are equally weighted, and the strategies are to buy stocks in the top decile and sell stocks in the bottom decile. The minimum acceptable return for the Sortino ratio is set to zero for Long/Short (L-S) portfolios and to the Libor rate for L or S portfolios.
Source: Compustat, Bloomberg, Barclays Research

To check whether the BEAM performance is driven by sector allocation, we look at the outperformance of BEAM over Momentum when stocks are sorted across the whole universe and within industries. Figure 5 displays the trailing 12-month outperformance of BEAM over momentum between 1999 and 2018. The key finding is that being industry-neutral considerably increases BEAM outperformance over momentum, and reduces the outperformance volatility.

FIGURE 5

Trailing 12-month outperformance of BEAM over Momentum

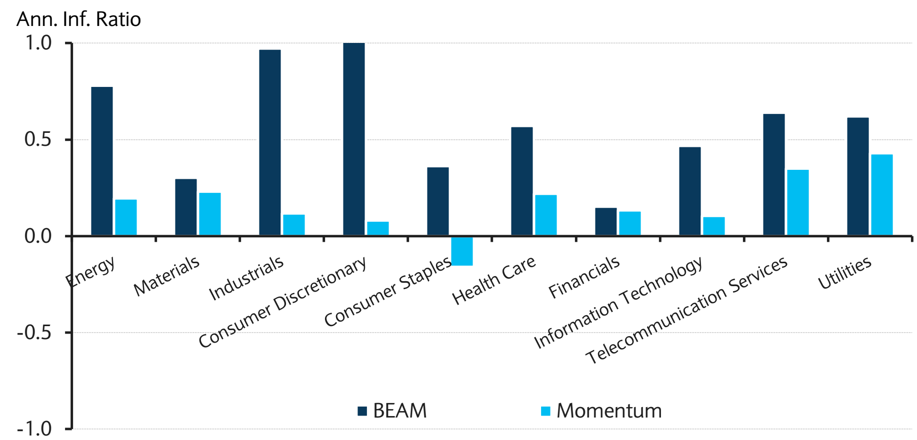


Source: Compustat, Bloomberg, Barclays Research

To check whether BEAM and Momentum performance are driven by sector allocation, Figure 6 reports the annualized information ratio of those strategies in each of the 10 GICS (2-digit) sectors. Within each industry, we sort stocks in two groups based on past corporate bond excess returns or past stock returns. These strategies consist of buying past winners and selling past losers. BEAM has positive information ratios in all sectors, with an average information ratio of 0.6, ranging between 0.15 for financials and 1.16 for consumer discretionary. In contrast, the information ratios for momentum portfolios are lower, with an average of 0.17, and ranging between -0.16 for consumer staples and 0.43 for utilities. Moreover, BEAM information ratios are larger than those of momentum in all sectors, except financials where the information ratios of BEAM and momentum are about the same. This evidence suggests that BEAM can enhance performance also for investors that face industry constraints. This finding also indicates that BEAM strategy returns are not driven by sector effects.

FIGURE 6

BEAM and Momentum Annualized Information Ratio by GICS Sector



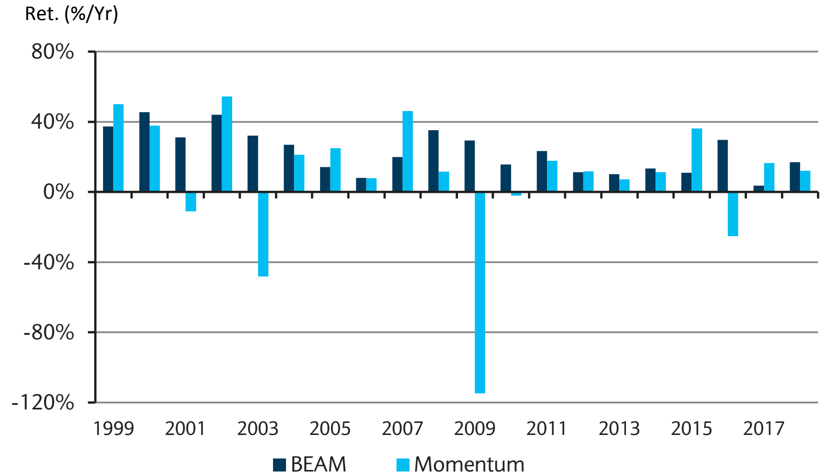
Source: The sample period is January 1999 to August 2018. This figure plots the annualized information ratio for BEAM and momentum strategies. BEAM is based on a 3-month ranking window and Momentum on a 12-month ranking window skipping the most recent month. Each month stocks are sorted within each industry into two portfolios based on the BEAM and momentum signals, and held for one month. The portfolios are equally weighted, and the strategies are to buy stocks in the top portfolio and sell stocks in the bottom portfolio. GICS 2-digit sectors are used for BEAM and momentum portfolios.
Source: Compustat, Bloomberg, Barclays Research

Stability of the Performance over Time and by Market States

To examine the stability of the BEAM performance, Figure 7 plots the annualized BEAM and momentum returns by year. BEAM returns have always been positive since the start of the sample in 1999, ranging between 4% (in 2017) and 45% (in 2000). In contrast, Momentum profits have ranged between -115% (in 2009) and 54% (in 2002), and were negative in five years (2001, 2003, 2009, 2010 and 2016), so on average one year every four years. BEAM did not experience any Momentum crashes, which mostly coincides with periods of rapid market reversals from severe troughs (as already noted in Figure 3). Importantly, the volatility of BEAM returns has been one-third of the volatility of Momentum (i.e., 14% and 37%, respectively, as reported in Figure 4 for the sample 1999-2018).

FIGURE 7

BEAM and Momentum Returns by Year



Note: The sample period is January 1999 to August 2018. This table displays the annualized average returns for industry-neutral BEAM and Momentum by year. BEAM is based on a 3-month ranking window and Momentum on a 12-month ranking window skipping the most recent month. The annualized returns correspond to the (arithmetic) average monthly returns multiplied by 12. The portfolios are equally weighted, and the strategies are to buy stocks in the top decile and sell stocks in the bottom decile. To construct industry-neutral portfolios, fixed income industries are used for BEAM and GICS 2-digit sectors are used for momentum.
Source: Compustat, Bloomberg, Barclays Research

Some anomalies display a strong seasonal component. For instance, most of the returns related to size seem to occur in January, and to disappear the rest of the year (Reinganum, 1983). Figure 8 reports the estimation results of regressing BEAM returns on monthly dummies, and controlling for a number of risk factors reported in the column headers.[4] In any given month, one of the seasonal dummies equals 1, and all the others equal 0. A detailed description of the risk factors, including their construction methodology, is provided in the next section. The last row reports the p-value associated to testing the null hypothesis that the monthly effects are equal across months.

We start by describing the results of the first column (i.e., “No Controls” case). BEAM returns are positive in every month, and are significantly different from zero most of the times. The estimated coefficient corresponds to the average BEAM return in that month. For instance, the average BEAM return in January is 0.98%. Although there is some variation from month to month, the hypothesis that the monthly effects are the same different across months cannot be rejected (the associated p-value is 22%). These findings are robust to control for various risk models. Specifically, the coefficients of the monthly dummies remain very similar across columns, and the null hypothesis can never be rejected at standard confidence level.

[4] In the interest of space, we do not report the factor loadings, as they are very similar to those reported in Figure 14.

FIGURE 8

Testing for Monthly Effects

	BEAM Returns (L/S, EW, Within industries) Controlling for:							
	No Controls	CAPM	FF3	FF3+Mom	FF3+Mom +STRev	FF3+Mom +Liq	FF3+QMJ+ BAB	FF5
January	0.98	0.90	0.90	1.32	1.92**	1.35	0.78	0.71
February	1.17*	1.13*	1.05*	0.49	0.51	0.45	0.75	0.55
March	1.10	1.41*	0.99	0.83	0.95	0.93	0.72	0.89
April	2.73***	3.04***	2.63***	3.10***	2.98***	3.21***	2.71***	2.57**
May	1.00	1.06	0.92	0.94	0.84	0.86	0.73	0.91
June	2.34***	2.26***	2.33***	1.73**	1.78**	1.72**	1.98**	2.53***
July	2.35**	2.43***	2.07**	1.90**	2.26**	2.25**	1.84**	1.77*
August	2.41***	2.41**	2.23**	2.27**	2.40**	2.25**	2.03**	1.97**
September	3.67***	3.45***	3.49***	3.17***	3.17***	3.04***	3.21***	3.18***
October	1.64	1.97*	1.95*	1.73	1.96*	1.87*	1.47	1.78
November	2.66**	2.92**	2.84**	2.60**	2.52**	2.63**	2.34**	2.54**
December	1.10**	1.40**	1.25*	0.73	0.84	0.72	1.17	1.41**
Adj. R^2	-0.3%	3.6%	6.3%	13.7%	15.4%	14.4%	7.3%	9.8%
H_0: Coefficients are equal (p-value)	0.22	0.16	0.15	0.07	0.10	0.10	0.24	0.22

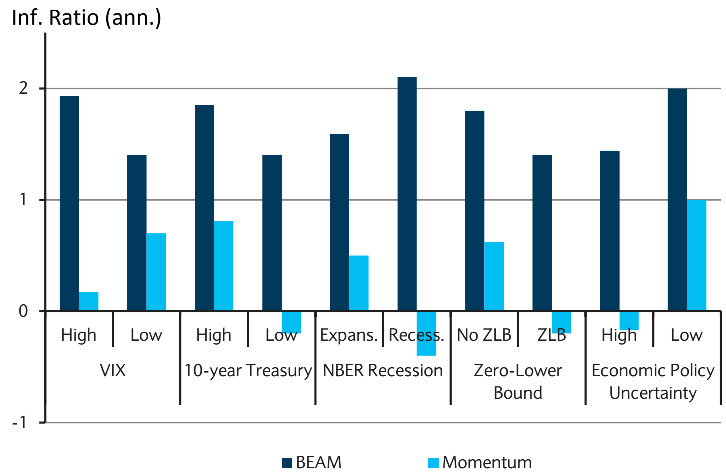
Note: The sample period is January 1999 to August 2018 (or data availability). The dependent variable is BEAM portfolio returns, long-short, equally weighted, within industries, and based on a 3-month ranking window. The explanatory variables are monthly dummies and additional controls indicated in the column headers. "FF3" and "FF5" stand for Fama-French 3- and 5-factor model. "Mom", "STRev", "Liq", "QMJ", "BAB" stand for momentum, short-term reversal, liquidity, quality minus junk and betting against beta factors. A description of these risk factors is provided in the "Combining Portfolios" Section reported below. The last row reports the p-value associated to testing the null hypothesis that the monthly effects are equal across months. The superscripts ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively, and are based on autocorrelation-consistent Newey-West standard errors.

Source: Compustat, Bloomberg, Kenneth French data library, Barclays Research

We now analyze BEAM performance in different economic states, rather than in calendar time (i.e., years or months). Figure 9 reports BEAM and momentum annualized information ratios depending on (i) the level of VIX (above or below the median, 18.3% in the sample 1999-2018); (ii) the level of the 10-year Treasury rate (above or below the median, 3.6% in 1999-2018); (iii) NBER recession vs. expansion; (iv) period when the fed funds target rate was stuck at zero (zero-lower bound, i.e., from December 2008 to December 2015) versus normal times; and (v) the level of the Economic Policy Uncertainty index computed in Baker, Bloom and Davis (2016; above or below the median, 102.4 in 1999-18). Of note, Figure 9 shows that the BEAM information ratio is always positive and higher than the momentum information ratio in every market condition. For instance, BEAM information ratio is around 2 both when expected equity volatility, measured by the VIX, is high, as well as when expected equity volatility is subdued. Furthermore, the BEAM information ratio displays lower dispersion across states compared to that of momentum strategy. These findings are especially relevant in the current economic environment characterized by rising Treasury yields and by bouts of stock market volatility (most recently in February 2018 and October 2018).

FIGURE 9

BEAM and Momentum Information Ratio in Different Market Conditions



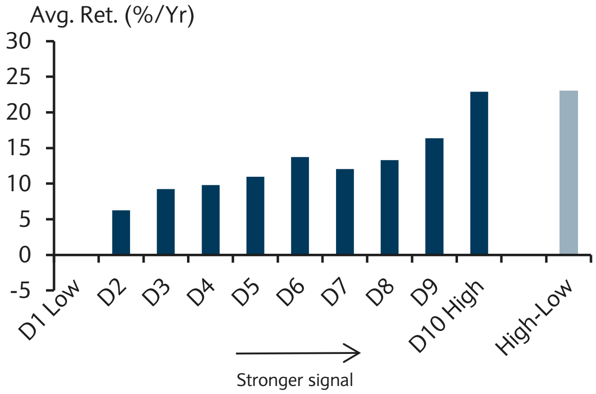
Note: The sample period is January 1999 to August 2018. This table displays the information ratio for BEAM and momentum in different market states. BEAM is based on a 3-month ranking window and Momentum on a 12-month ranking window skipping the most recent month. The High (Low) level of VIX is above (below) its median (18.1% in the sample 1999-18). The High (Low) level of the 10-year Treasury rate is above (below) its median (3.6% in 1999-18). The recession and expansion are classified by the NBER. The Zero Lower Bound period is from December 2008 to December 2015. The High (Low) level of Economic Policy Uncertainty computed in Baker, Bloom and Davis (2016) is above (below) its median (102.7 in the sample 1999-18). BEAM is based on a 3-month ranking window and Momentum on a 12-month ranking window skipping the most recent month. The portfolios are equally weighted, and the strategies are to buy stocks in the top decile and sell stocks in the bottom decile. To construct industry-neutral portfolios, fixed income industries are used for BEAM and GICS 2-digit sectors are used for momentum.
Source: Compustat, Bloomberg, Barclays Research

Hedging Efficacy of Long and Short Sides

Many theories in finance imply monotonic patterns between securities' risk or characteristics and expected returns. For instance, the Capital Asset Pricing Model (CAPM) posits higher average returns for stocks with higher betas. Another theory, the so called the liquidity-adjusted CAPM, implies that the expected return of a security increases with its expected illiquidity (Acharya and Pedersen, 2005). This section explores whether such a monotonicity pattern exists between the strength of the BEAM signal and the average returns of the ten decile portfolios. Figure 10 plots the BEAM returns by portfolio decile, as well as the high-minus-low (BEAM) portfolio return. Decile returns are mostly increasing with the strength of the BEAM signal, with higher signals being associated to higher returns. Although monotone, the relationship between the BEAM signal and portfolio returns is not linear, and it flattens from the third to the eighth decile portfolios.

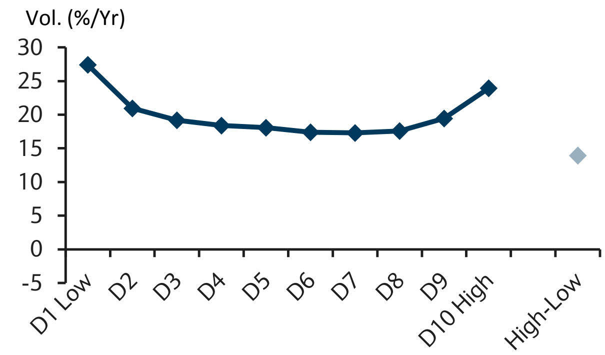
One possible explanation of the BEAM's outperformance compared with Momentum can be that the BEAM signal is related to the "low-volatility" anomaly, namely the fact that portfolios of low-volatility stocks have higher risk-adjusted returns than portfolios with high-volatility stocks (Blitz and van Vliet, 2007). In other words, the source of BEAM's performance may rise from overweighting low volatility stocks and underweighting high volatility stocks. To shed light on this hypothesis, we check whether there is a monotonic decreasing relation between the intensity of the BEAM signal and the volatility of the associated portfolio. Figure 11 plots the volatility of all bond-ranked decile portfolios, as well as the volatility of the top minus the bottom (BEAM) decile. We find that the volatilities of the bond-ranked portfolios for deciles two to nine are similar to each other. The volatility of the bottom and top portfolios is somewhat higher. This finding suggests that BEAM strategy is not a restatement of the low-volatility anomaly. In the next section, we further investigate whether there is a significant positive relationship between BEAM returns and low-vol portfolio returns.

FIGURE 10
Returns of Bond-ranked Portfolio Deciles



Note: The sample period is January 1999 to August 2018. This figure plots average annualized returns of all bond-ranked decile portfolios, as well as the high-minus-low (BEAM) portfolio return. Returns are equally weighted, based on a 3-month ranking window, and ranked within industries.
Source: Compustat, Bloomberg, Barclays Research

FIGURE 11
Volatility of Bond-ranked Portfolio Decile Returns



Note: The sample period is January 1999 to August 2018. This figure plots the annualized volatility of all bond-ranked decile portfolios, as well as the volatility of the top minus the bottom (BEAM) decile. Returns are equally weighted, based on a 3-month ranking window, and ranked within industries.
Source: Compustat, Bloomberg, Barclays Research

Specifically, we look at the extent to which BEAM returns remain positive after controlling for the low-versus–high beta factor of Frazzini and Pedersen (2014), which represents a sophisticated modern version of Black’s (1972) beta-arbitrage strategy.

An interesting finding displayed in Figure 11 is that the combination of top and bottom decile in a long-short portfolio results in a lower volatility for BEAM compared with each individual portfolio. This result suggests that top and bottom bond-ranked deciles hedge each other effectively. Indeed, as discussed in Ben Dor and Xu (*2014*), the beta (i.e., a measure of the systematic risk of a portfolio with respect to the market) of the top and bottom decile portfolio is similar to each other, respectively 1.5 for the bottom and 1.3 for the top decile. Hence, the beta of BEAM is close to zero.

Implementing BEAM in Practice

Combining Portfolios

This section investigates whether BEAM returns are explained by exposures to commonly used asset pricing factors. First, we look at correlations, which measure the bivariate relation between pairs of variables. Then, we look at a multivariate analysis, where we also control for the comovements between BEAM returns and other risk factors.

Figure 12 reports the time-series correlations between monthly returns of a host of widely accepted and used risk factors, such as:

- The market excess return (Mkt_Rf) the size factor (SMB, the return spread of small minus large stocks).
- The value factor (HML, the return spread of cheap minus expensive stocks).
- The investment factor (CMA, return spread of firms that invest conservatively minus aggressively).
- The profitability factor (RMW, the return spread of the most profitable firms minus the least profitable).

- The Momentum factor (Mom, the return spread of being long winners and short losers of the past 12 months and skipping the most recent month).
- The short-term reversal factor (ST_REV, the return spread of being long losers and short winners of the most recent month).
- The Pastor and Stambaugh (2003) traded liquidity factor (Liq, the return spread of being long companies with large historical liquidity betas and being short companies with low liquidity betas).
- The quality factor (QMJ, the return spread of going long high-quality stocks and short low-quality stocks).
- The betting-against-beta factor (BAB, the return spread of holding leveraged low-beta stocks and shorting de-leveraged high-beta stocks).[5]

The last two portfolios, an industry-neutral Momentum and BEAM (Mom within Ind. and BEAM within Ind., respectively), differ from the other factors along two dimensions. First, the portfolios are industry-neutral: loser and winner stocks are defined based on their performance relative to their industries. Second, the underlying stock universe comprises companies that have outstanding bonds in the Bloomberg-Barclays bond index, rather than the overall CRSP equity universe.

The market, size and value factors have been staples of modern asset pricing models used in the literature since Fama and French (1993). The momentum, short-term reversal and liquidity factors have also been extensive used for many years (Jegadeesh and Titman, 1993; Jegadeesh, 1990; and Pastor and Stambaugh, 2003). On the other side, the remaining four risk factors we consider have been proposed around the same time that the original BEAM was published. This allows us to take a fresh look at the risk-adjusted performance of BEAM using the latest insights in empirical asset pricing. Furthermore, it allows us to examine whether BEAM returns have a common source with other not-yet-published characteristic portfolios.

Figure 12 reports two types of correlation measures. The elements in the upper triangular matrix represent the Pearson product-moment correlation, and it is designed to measure the strength of a linear relation between the two variables. The elements in the lower triangular matrix represent the rank (Spearman) correlation, and it is designed to detect monotonicity in the relationship between the two variables. Diagonal entries, which represent the correlation between a variable and itself (and equal 1 by definition) are left blank. To enhance the clarity of the table, we overlay it with a heat map, where dark colours indicate a large (in absolute value) correlation coefficient.

We focus on the results based on the Pearson correlation, as both measures of correlation lead to the same conclusions. Moreover, this latter finding that the coefficients above the diagonal are quite similar to those below the diagonal indicates correlations are robust to the presence of potentially large portfolio returns. The correlation between the momentum factor based on the CRSP universe and the momentum factor based on the BEAM universe is above 80%. This suggests that restricting the sample to companies that have underlying bonds in the Bloomberg-Barclays index does not affect the momentum returns. BEAM portfolio returns display very low correlation with other factor returns, and ranges between 30% (with momentum) and -33% (with short-term reversal). These findings show that BEAM is not spanned by existing factors, and there may be potential diversification benefits when BEAM is combined with other factors.

[5] The QMJ factor measures the firm's quality, and is based on four sub-components: profitability, profit growth, safety, and payout (Asness, Frazzini and Pedersen, 2013). The BAB factor captures the low- versus high-beta stocks (Frazzini and Pedersen, 2014). The CMA and RMW factors proxies quality factors, respectively investment growth and profitability (Fama and French, 2015).

FIGURE 12

Correlation matrix

	CRSP Universe										BEAM Universe	
	Mkt_Rf	SMB	HML	CMA	RMW	Mom Fama-French	ST_Rev	Liq	QMJ	BAB	Mom Within Ind.	BEAM Within Ind.
Mkt_Rf		0.04	-0.31	-0.07	-0.31	-0.26	0.27	0.18	-0.70	-0.38	-0.42	-0.21
SMB	0.08		0.09	0.51	-0.69	-0.37	0.27	0.14	-0.44	-0.09	-0.27	-0.07
HML	-0.29	0.23		0.46	0.44	0.02	-0.20	-0.03	0.22	0.56	0.00	0.23
CMA	-0.03	0.43	0.45		-0.24	-0.03	-0.14	-0.07	-0.12	0.08	0.01	0.21
RMW	-0.35	-0.54	0.28	-0.18		0.42	-0.30	-0.11	0.63	0.48	0.28	0.18
Mom Fama-French	-0.20	-0.28	-0.13	-0.09	0.38		-0.53	0.00	0.44	0.30	0.83	0.30
ST_Rev	0.33	0.26	0.00	0.13	-0.32	-0.40		0.06	-0.29	-0.28	-0.39	-0.33
Liq	0.10	0.15	-0.05	-0.09	-0.09	0.08	0.04		-0.18	0.06	-0.01	-0.12
QMJ	-0.67	-0.38	0.10	-0.11	0.58	0.36	-0.40	-0.15		0.46	0.51	0.26
BAB	-0.35	0.08	0.43	0.08	0.31	0.18	-0.17	0.00	0.37		0.36	0.19
Mom Within Ind.	-0.41	-0.15	-0.02	0.00	0.21	0.72	-0.29	0.07	0.38	0.27		0.30
BEAM Within Ind.	-0.10	0.08	0.13	0.15	0.00	0.19	-0.19	-0.03	0.11	0.14	0.26	

Note: The sample period is January 1999 to August 2018 (or data availability). The table reports the correlation matrix of monthly returns between various risk factors. "Mkt_Rf" stands for the market excess return, "SMB" stands for the size factor, "HML" stands for the value factor, "CMA" stands for the investment factor, "RMW" stands for the profitability factor, "Mom" stands for the momentum factor. "ST_Rev" stands for Short-term reversal. Those risk factors are all based on CRSP U.S. stock universe. The portfolios are equally weighted, and the strategies are to buy stocks in the top decile and sell stocks in the bottom decile. "Liq" stands for the Pastor and Stambaugh (2003) traded liquidity factor (available until December 2017). "QMJ" stands for the quality factor (Asness, Frazzini and Pedersen, 2013), and "BAB stands for the "betting-against-beta" factor (Frazzini, and Pedersen, 2014), and both factors are available until July 2018. "Mom Within Ind." and "BEAM Within Ind." stand for an industry-neutral momentum and BEAM portfolio. BEAM uses a three-month ranking windows, and momentum a 12-month ranking window, skipping the most recent month. The level (Pearson) correlation is reported in the upper triangular matrix, the rank (Spearman) correlation is reported in the lower triangular matrix.
Source: Compustat, Bloomberg, AQR and Kenneth French data library, Barclays Research

Next, we use a time-series (multivariate) regression framework to test whether BEAM returns are explained by exposures to those asset pricing factors introduced above. Using OLS with Newey-West standard errors, we estimate:

$$r_t = \alpha + \boldsymbol{\beta}' \mathbf{F}_t + \varepsilon_t$$

where r_t is the long-short BEAM and momentum portfolio returns, α is the portfolio's alpha, $\mathbf{F}_t$ is a vector of stock market risk factors, and ε_t represents a residual risk that is unrelated to the factors. Stocks are ranked across the whole universe (first two columns) or within industries (last two columns). Significant abnormal returns indicate that an investor already trading the factors $\mathbf{F}_t$ could realize significant gains by starting to trade the strategy r_t. In contrast, insignificant abnormal returns indicate that the investor has little to gain by getting exposure to the r_t strategy.

Figure 13 presents alpha coefficients from the time-series regressions for the sample period January 1999 to August 2018. The first row reports the raw returns, which correspond to the average returns over the full sample period. We consider seven risk models: the CAPM (second row), the Fama-French 3 factor model (third row; FF3), the FF3 combined with momentum (fourth row; FF3+Mom), the FF3 combined with momentum and short-term reversal (fifth row; FF3+Mom+STRev), the FF3 combined with momentum and liquidity (sixth row; FF3+Mom+Liq), the FF3 combined with quality and betting-against-beta factors (seventh row; FF3+QMJ+BAB), and the Fama-French 5 factor model (last row, FF5). We indicate with stars when the coefficients are significant at the 10% level or better.

BEAM annualized returns have large and significant risk-adjusted alpha, ranging between 20% and 24% depending on the underlying risk model for industry-neutral portfolios and between 21% and 27% for portfolios ranked across the overall stock universe. Therefore, BEAM returns are unaffected by adjustment for common risk factors. The performance of momentum is lower than that of BEAM, both unconditionally and after controlling for other risk factors. For instance, the industry-neutral momentum average return ranges between 7% and 18%, compared with a raw return of 8%.

FIGURE 13

Risk-adjusted alpha based on various risk models

Alpha (%/Yr) based on	Full Sample: 1999 -2018			
	Across industries		Within industries	
	BEAM	Mom	BEAM	Mom
Raw returns	25.9***	14.5	23.1***	8.2
CAPM	27.4***	20.2**	24.3***	13.0**
FF3	24.8***	24.6***	22.9***	18.0***
FF3+Mom	22.4***	10.7**	21.1***	8.5**
FF3+Mom+STRev	25.9***	9.6**	22.4***	7.0**
FF3+Mom+Liq	23.1***	11.1**	21.7***	8.8***
FF3+QMJ+BAB	22.1***	10.8	19.9***	9.4
FF5	21.1***	17.0*	21.0***	13.4**

Note: The sample period is January 1999 to August 2018 (or data availability). The table reports the intercept (annualized risk-adjusted alpha) of the regression of the BEAM and equity momentum strategies on various risk factors. "FF3" and "FF5" stand for the Fama and French 3- and 5-factor model, respectively. "FF3+Mom" stands for the Fama-French 3-factor model augmented by momentum (stock's cumulative return for t-12 to t-2). "ST Rev" stands for Short-term reversal, and captures the cross-sectional, negative, relation between current stock returns and one-month lagged returns. "Liq" stands for the Pastor and Stambaugh (2003) traded liquidity factor, available until December 2017. "QMJ" stands for the quality factor (Asness, Frazzini and Pedersen, 2013), and "BAB stands for the "betting-against-beta" factor (Frazzini, and Pedersen, 2014), and both factors are available until July 2018. Those risk factors are all based on CRSP U.S. stock universe. The portfolios are equally weighted, and the strategies are to buy stocks in the top decile and sell stocks in the bottom decile. For within-industry ranking, fixed income industries are used for BEAM and GICS 2-digit sectors are used for momentum. The econometric method is Ordinary Least Squares. The superscripts ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively, and are based on autocorrelation-consistent Newey-West standard errors.

Source: Compustat, Bloomberg, AQR and Kenneth French data library, Barclays Research

To understand how BEAM returns are related to other risk factors, Figure 14 reports the factor loadings for the seven risk models described above, and where the dependent variable is the industry-neutral BEAM. By construction, the first row corresponds to the third column of Figure 13. The key finding is that BEAM returns have very low factor loadings, indicating that the BEAM strategy is not spanned by other risk factors. The largest adjusted R^2, for the risk model FF3+Mom+STRev, is only 15%, indicating that most of the time-series variation of BEAM returns remains unexplained. All in all, these findings suggest that BEAM not only generates a large and significant alpha, but also adds diversification benefits.

FIGURE 14

Factor loadings

	Dep. Var is BEAM (EW, Within Industries)						
	CAPM	FF3	FF3+Mom	FF3+Mom +STRev	FF3+Mom +Liq	FF3+QMJ +BAB	FF5
Intercept	24.3***	22.9***	21.1***	22.4***	21.7***	19.9***	21.0***
Mkt - Rf	-0.20**	-0.14	-0.07	-0.06	-0.05	0.00	-0.14
SMB		-0.07	0.02	0.04	0.03	0.01	-0.13
HML		0.16	0.17**	0.15*	0.18**	0.17*	0.02
Mom			0.15***	0.10**	0.15***		
STRev				-0.11*			
Liq					-0.11		
QMJ						0.31*	
BAB						-0.02	
CMA							0.32***
RMW							0.06
Adj. R^2	4.0%	6.6%	13.2%	15.0%	13.9%	7.7%	9.9%

Note: The sample period is January 1999 to August 2018 (or data availability). The table reports the regression results of BEAM returns on various risk factors. "Mkt - Rf" stands for the market excess returns. "SMB" stands for the size factor. "HML" stands for the value factor. "Mom" stands for the momentum factor. "STRev" stands for short-term reversal factor. "Liq" stands for the Pastor and Stambaugh (2003) traded liquidity factor, and it is available until December 2017. "QMJ" stands for the quality factor (Asness, Frazzini and Pedersen, 2013), and "BAB stands for the "betting-against-beta" factor (Frazzini, and Pedersen, 2014), and both factors are available until July 2018. "CMA" stands for the investment factor. "RMW" stands for the profitability factor. Those risk factors are all based on CRSP U.S. stock universe. The portfolios are equally weighted, and the strategies are to buy stocks in the top decile and sell stocks in the bottom decile. For within-industry ranking, fixed income industries are used for BEAM and GICS 2-digit sectors are used for momentum. The econometric method is Ordinary Least Squares. The superscripts ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively, and are based on autocorrelation-consistent Newey-West standard errors.

Source: Compustat, Bloomberg, AQR and Kenneth French data library, Barclays Research

Another way to assess the potential value of BEAM to real investors is to consider the incremental information ratio that could have been achieved using that strategy. Figure 15 shows the information ratios of the Fama and French three-factor model (Mkt-Rf, SMB, HML), momentum (Mom) and short-term reversal (ST Rev) strategies (in columns 1 to 6) for the sample period 1999 – 2018. The last four columns report the portfolio weights of ex-post mean-variance efficient portfolios of various combinations of those strategies. Specifically, columns 7 and 8 consider the Fama and French three-factor model (FF3) and columns 9 and 10 consider FF3 augmented by momentum and short-term reversal. Columns 8 and 10 add BEAM to the opportunity set of investable assets considered in columns 7 and 9.

All six strategies provide positive information ratios. The performance of the momentum factor is, however, lower than the performance of the market factor. This result is driven by the momentum crash experienced in 2008-2009, where most of the momentum gains have been dissipated. Combining factors generates higher information ratios, thus confirming the basic tenant of modern portfolio theory, where efficient combinations of high Sharpe ratio assets have even higher Sharpe ratios. The performance improvement stems mostly from a reduction in volatility without any sacrifice in returns. Adding BEAM to the investable set roughly doubles the information ratio, from 0.90 to 1.93 for the FF3 portfolio and from 1.20 to 2.13 for the FF3+Mom+STRev portfolio. BEAM substantially increases the portfolio returns without affecting the risk. The importance of including BEAM as an additional risk factor can also be seen by the large weight, around 50%, in the overall portfolio.

FIGURE 15

Ex-post mean-variance efficient portfolios

Strategy weight in ex-post MVE portfolio and portfolio Inf. Ratio										
	Single Asset						FF3		FF3+Mom+ST Rev	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mkt - Rf	1						0.37	0.23	0.22	0.15
SMB		1					0.16	0.11	0.12	0.05
HML			1				0.47	0.09	0.31	0.10
Mom				1					0.16	0.04
ST Rev					1				0.19	0.16
BEAM						1		0.57		0.49
Avg. Ret. (%/Yr)	5.9	6.6	9.2	4.8	9.5	23.1	7.6	16.1	7.5	15.3
Vol. (%/Yr)	14.9	16.5	15.6	27.8	22.1	13.9	8.4	8.4	6.3	7.2
Inf. Ratio (ann.)	0.40	0.40	0.59	0.17	0.43	1.66	0.90	1.93	1.20	2.13

Note: The sample period is January 1999 to August 2018. The table reports the portfolio weights in the ex-post mean-variance efficient portfolio for Fama and French three-factor model (Mkt-Rf, SMB, HML), momentum (Mom) and short-term reversal (ST Rev) strategies. Those risk factors are all based on CRSP U.S. stock universe. BEAM portfolio is equally weighted and industry-neutral, and consists of buying stocks in the top decile and selling stocks in the bottom decile.

Source: Compustat, Bloomberg, Kenneth French data library, Barclays Research

Conditional Double Sort

Momentum and BEAM are positively related, and short-term reversal and BEAM are negatively related. To better understand the interactions between BEAM on one side and stock momentum and short-term reversal signals on the other side, we perform a conditional double-sort. We view this exercise as a complementary, non-parametric, test of the correlation results reported in Figure 12. Panel A of Figure 16 reports the results for BEAM and momentum, and Panel B for BEAM and last month equity return. To illustrate the double-sorting methodology, consider the "BEAM x Momentum" table in Panel A. We proceed in two steps. First, stocks are assigned to three buckets based on BEAM signals. Then, within each bucket stocks are further assigned to three Momentum buckets. The column "H-L" reports the return differential between high and low Momentum portfolios. This procedure generates the "BEAM x Momentum" panel. To produce the "Momentum x BEAM" panel, we perform the same double-sorting described above, where we sort first on Momentum, and then on BEAM.

We find that conditioning on the BEAM signal improves all Momentum terciles. Specifically, the last column of Figure 16 shows that the returns range between 7% and 14%, and the annualized Information ratio of BEAM high/low returns is above 0.9. In contrast, reversing the sorting order (i.e., sorting first on BEAM and then on Momentum) does not lead to a consistent performance improvement. The increase in the Momentum signal only leads to monotonic increase in returns in the low BEAM portfolio tercile, and generates an annualized information ratio of 0.45. Put differently, controlling for BEAM when constructing equity momentum strategies improves their performance by increasing returns and decreasing volatility. In contrast, BEAM performance is not systematically affected by controlling for equity momentum strategy.

The bottom part of Figure 16 looks at the interaction between BEAM and last month equity return. When sorted within BEAM first, stocks with low last month returns do not consistently outperform stocks with high last month returns. Within each last-month-return bucket, high BEAM stocks consistently have higher average returns than low BEAM stocks. Specifically, H-L BEAM annualized returns range from 10.8% to 15.3%, and its information ratios range between 1.25 and 1.52.

FIGURE 16

Performance with conditional double sort: BEAM, Momentum and Last Month Equity Return

Panel A: BEAM and Momentum

	BEAM x Momentum					Momentum x BEAM				
		Conditional Sort on Momentum					Conditional Sort on BEAM			
	First Sorting Dimension	Low	Medium	High	H-L	First Sorting Dimension	Low	Medium	High	H-L
Avg. Ret (%/Yr)	Low BEAM	0.9	6.3	9.4	8.4	Low Momentum	1.7	9.7	15.7	14.0
Vol. (%/Yr)		29.6	20.5	17.4	18.8		29.7	24.2	25.9	11.4
Sharpe (Inf.) Ratio (Ann.)		0.03	0.31	0.54	0.45		0.06	0.40	0.60	1.22
Avg. Ret (%/Yr)	Medium BEAM	11.8	11.4	11.8	-0.1	Medium Momentum	8.5	11.5	15.3	6.8
Vol. (%/Yr)		22.3	15.9	16.1	13.2		18.8	16.7	17.9	7.5
Sharpe (Inf.) Ratio (Ann.)		0.53	0.71	0.73	0.00		0.45	0.69	0.86	0.91
Avg. Ret (%/Yr)	High BEAM	16.3	16.7	17.8	1.5	High Momentum	8.9	13.0	17.7	8.8
Vol. (%/Yr)		26.2	18.3	17.3	16.8		17.0	16.0	17.2	6.9
Sharpe (Inf.) Ratio (Ann.)		0.62	0.91	1.03	0.09		0.52	0.81	1.03	1.28

Panel B: BEAM and Last Month Equity Return

	BEAM x Last Month Equity Return					Last Month Equity Return x BEAM				
		Cond. Sort on Last Month Equity Return					Conditional Sort on BEAM			
	First Sorting Dimension	Low	Medium	High	H-L	First Sorting Dimension	Low	Medium	High	H-L
Avg. Ret (%/Yr)	Low BEAM	4.3	6.0	5.0	0.7	Low Last Month Return	2.6	13.2	17.8	15.3
Vol. (%/Yr)		28.0	20.4	20.3	12.1		27.9	21.6	23.0	11.0
Sharpe (Inf.) Ratio (Ann.)		0.15	0.29	0.25	0.06		0.09	0.61	0.77	1.39
Avg. Ret (%/Yr)	Medium BEAM	15.0	11.3	9.1	-5.8	Medium Last Month Return	6.0	11.2	17.6	11.6
Vol. (%/Yr)		20.9	16.8	17.5	8.7		19.3	17.1	18.7	7.6
Sharpe (Inf.) Ratio (Ann.)		0.72	0.67	0.52	-0.67		0.31	0.66	0.95	1.52
Avg. Ret (%/Yr)	High BEAM	17.1	18.2	16.8	-0.3	High Last Month Return	6.1	10.6	16.9	10.8
Vol. (%/Yr)		22.7	18.7	21.0	9.6		20.4	17.4	21.4	8.6
Sharpe (Inf.) Ratio (Ann.)		0.75	0.97	0.80	-0.03		0.30	0.61	0.79	1.25

Note: The sample period is January 1999 to August 2018. The BEAM and momentum portfolios are equally weighted, based on terciles, and ranked within industries. BEAM uses a three-month ranking windows, momentum a 12-month ranking window, skipping the most recent month, and last month equity return uses a one-month ranking window.

Source: Compustat, Bloomberg, Barclays Research

In sum, irrespective of the methodology used (see, e.g., Figure 12 and Figure 16), BEAM signal is not subsumed by either Momentum or short-term reversal strategies.

Combining Signals: BEAM Signal Looks Superior Despite Partial Universe Coverage

There is considerable diversification benefit from combining momentum and BEAM strategies (Figure 15). BEAM signals are, however, only available for a subset of equities, i.e., the universe of companies that issue bonds that are included in the Bloomberg-Barclays index. To test the informativeness of BEAM signals on a full equity space, we investigate whether BEAM signals enhance stocks momentum signals for the Russell 1000 universe. We consider two methods to combine the BEAM and momentum signals. Method 1 uses the BEAM signal when is available, and the stock Momentum signal when BEAM is not available. Method 2 uses the average of the BEAM and Momentum signals when the BEAM signal is available, and the Momentum signal when BEAM is not available.

Figure 17 reports the long-short, long and short portfolios for four sets of signals: stock Momentum only (left panel), BEAM and Momentum combined signals (middle panels) and BEAM only (right panel). The top rows consider strategies where stocks are ranked across the whole universe, whereas the bottom rows consider strategies where stocks are ranked within industries. Method 1 produces higher information ratio and lower volatility than using Momentum only. Method 2 does not improve the information ratio as much as Method 1. One possible explanation is that Method 2 relies less on the BEAM signal, and thus dilutes its effectiveness.

An important benefit of combining BEAM and Momentum signal is the substantial reduction of the worst monthly return and the maximum drawdown. For instance, by using Method 1 and ranking companies within industries, the maximum drawdown becomes -43%, compared with -74% when based only on the Momentum signal. In other words, the information benefit of using BEAM is especially pronounced during panic states. As these periods are particularly hard to predict, BEAM signals act as a “free” insurance policy. By including BEAM, the average return is roughly similar to that of Momentum, but the tail risk is limited.

The right panel of Figure 17 shows the performance of the BEAM signal using the same number of companies (i.e., 100 stocks for the long-leg and 100 for the short-leg of the portfolio) as those used in the other strategies. The deterioration of the BEAM performance can be ascribed to two reasons. The Russell 1000 index represents the largest companies in the U.S. stock market. Although the BEAM universe has a tilt on large-cap firms, it also contains a few companies that belong to the Russell 2000 index (on average 10% of the number of stocks and about 15% in terms of market capitalization; see Ben Dor, Guan and Rosa, 2018, for more details). Hence, there is a size premium component.[6] An economic rationale for this premium is that the informational value of bond signals is higher for small stocks, namely for stocks that tend to have a lower analysts’ coverage. Second, the number of companies included in each decile is fixed at 100 for the whole sample period. At the start of the sample, in 1999, the number of companies of the BEAM universe that have publicly traded common stocks is about 700. This implies that the size of the decile corresponds to a quintile of the results reported in Figure 1. Although average BEAM decile returns are monotone with the strength of the BEAM signal (see discussion below), the returns are concentrated in the extreme decile portfolios.

FIGURE 17

Russell 1000 Top/Bottom Decile Performance from using BEAM and Momentum Signals

		Momentum Only (Deciles)			BEAM and Momentum Combined Signals						BEAM Only (Top/Bottom 100 stocks)		
					Method 1			Method 2					
		L-S	L (D10)	S (D1)	L-S	L (D10)	S (D1)	L-S	L (D10)	S (D1)	L-S	L	S
Ranked across Universe	Avg. Ret. (%/Yr)	5.74	13.75	8.01	5.69	14.05	8.36	5.06	13.83	8.78	5.11	12.50	7.40
	Vol. (%/Yr)	33.14	24.11	35.67	21.74	22.86	30.59	30.14	23.63	34.03	11.84	19.52	22.34
	Inf. (Sharpe) Ratio (Ann.)	0.17	0.48	0.16	0.26	0.52	0.20	0.17	0.50	0.20	0.43	0.53	0.24
	Worst Monthly Ret (%)	-61.08	-30.46	-28.40	-40.81	-22.65	-27.24	-50.31	-30.64	-30.47	-15.70	-21.99	-24.25
	Max. Drawdown (%)	-82.18	-59.66	-83.80	-57.38	-64.52	-73.06	-78.64	-57.96	-80.14	-27.07	-61.33	-65.49
Ranked within Industry	Avg. Ret. (%/Yr)	2.98	11.98	9.01	4.84	13.51	8.67	4.59	12.70	8.11	6.74	14.17	7.43
	Vol. (%/Yr)	23.97	19.08	30.59	14.97	19.92	26.78	22.13	19.08	29.49	8.29	18.44	20.84
	Inf. (Sharpe) Ratio (Ann.)	0.12	0.52	0.22	0.32	0.57	0.24	0.21	0.55	0.20	0.81	0.65	0.25
	Worst Monthly Ret (%)	-55.09	-20.25	-27.00	-28.71	-20.41	-28.42	-45.11	-20.90	-27.90	-7.68	-21.69	-26.45
	Max. Drawdown (%)	-73.79	-56.21	-73.66	-42.67	-59.36	-72.49	-64.30	-54.36	-74.21	-13.44	-57.74	-68.84

Source: The sample period is January 1999 to August 2018. In Method 1, when BEAM is available, the BEAM signal is used, and when BEAM is not available, the Momentum signal is used. In Method 2, when BEAM is available, the average rank of the BEAM and Momentum signal is used, and when BEAM is not available, the Momentum signal is used. BEAM is based on a 3-month ranking window and Momentum on a 12-month ranking window skipping the most recent month. Each month stocks are sorted into deciles based on each of the four signals, and held for one month. The portfolios are equally weighted, and the strategies are to buy stocks in the top decile and sell stocks in the bottom decile. For within-industry ranking, fixed income industries are used for BEAM and GICS 2-digit sectors are used for momentum.
Source: Compustat, Bloomberg, Barclays Research

[6] Another manifestation of the size premium is that the returns of the equally-weighted BEAM portfolio are higher than those of the value-weighted portfolio (see, e.g., Figure 1).

Trading the BEAM Portfolio: Practical Aspects

Our analysis has focused on the expected gross returns of the BEAM strategy. Whether investors can benefit from the BEAM signal in practice, however, critically depends on the net of transaction cost returns. In this section we explore whether the BEAM strategy is implementable and sizeable, or whether it faces significant practical impediments that prevent investors from profiting from it. We evaluate the robustness of BEAM performance to trading costs and capacity limits by taking into consideration three implementation aspects: day and time of trade execution, price impact and shorting costs.

The bond signal usually becomes available on the last trading day of each month after the stock market close. To compute performance, the original BEAM study assumed, however, that equities are bought (sold) at the close price of the last trading day of the previous month, and sold (bought) at close of following month-end. This assumption is usually used in studies based on monthly frequency but it is not (strictly speaking) implementable since on the last trading day of each month the bond data are not available yet. We relax the assumption by trading stocks on the first (*D1*), second (*D2*) or third (*D3*) trading day of the next month, as opposed to the last trading day of the current month.

Another practical consideration is the time of the day when stocks are bought or sold. In our analysis we have relied on close prices. However, the BEAM signal is generated overnight, and hence it could have been delivered to the trading desk before market opens on the first day of the month. We use morning prices that are designed to approximate volume-weighted average price (VWAP) execution between 10 am and 12 pm ET.[7]

Price impact refers to the trading costs that occur when prices move systematically away from the trader's order (increasing before buy orders or decreasing before sell orders) between the time of a trade decision and complete execution of the order. The original study equally weighted all stocks, but positions in some stocks may be too big to trade without affecting the market. Instead of estimating a price-impact function, which is model-specific and whose output is subject to considerable estimation uncertainty, we prefer to err on the conservative side by imposing a trading constraint on the position in each stock relative to its average daily volume (ADV), and thus deviating from an equally weighted scheme. The simplifying assumption is that the price impact is negligible as long as the transaction size is below a given threshold (expressed as a percentage of ADV).

We consider two types of ADV constraints. We start with an equally weighted portfolio of $100mn, and impose a 5%, 10% or 15% ADV constraint, indicated under the column header "Execution with Daily Stock Position Limit (EW with ADV Constraint)". If a given stock exceeds the pre-defined limit, its excess position is allocated to other stocks with extra capacity. We also consider an alternative implementation procedure, indicated under the column header "Max Capacity Strategy (Position = 10% ADV)", where the weights on each stock correspond to the 10% of their ADV, instead of being equal to each other. The row in gray reports the average portfolio capacity (in $ mn) that could be implemented with this type of ADV constraint. In either case, we allow the portfolio formation to take place in one day ("Day 1"), over two ("Day 1 & 2") or three days ("Day 1, 2 & 3"). The multi-day implementation consists on allocating any position in excess of the ADV constraint to the same stock on the remaining (second and third) days, and then to other stocks with extra capacity if needed.

[7] The morning prices are calculated based on a combination of open and close prices. Formally, the historical morning price for company *i* are approximated by 0.42*Open Price$_i$ + 0.58*Close Price$_i$. The weights are determined by cross-sectional regression of VWAP prices between 10 am and 12 pm on the open and close prices of the same day using recent data from Bloomberg. We also investigate the sensitivity of the results to using open prices or close prices on the first (*D1*), second (*D2*) or third (*D3*) trading day, and the results remain very similar to those reported in Figure 18.

Trading BEAM portfolios requires taking 'short' positions in the 'losers' stocks, namely those stocks associated to corporate bonds with past bond returns that feature in the bottom decile of the population. Short positions are, however, more costly to establish and to maintain compared to long positions. We apply shorting cost as suggested by the existing literature (e.g., Henderson et al., 2017; Drechsler and Drechsler, 2017, and references therein).

Figure 18 shows the BEAM performance for various trading implementations. The first column reports the results corresponding to the baseline BEAM portfolio (i.e., close-to-close returns based on the last trading day of each month). The second to fourth columns consider different execution lags, from one to three days. The rest of the columns consider position limits. The top panel covers the original sample period from January 1999 to December 2013, and the bottom panel covers the out-of-sample period, i.e., after the publication of the paper.

We find that delaying execution decreases BEAM performance. In particular, for the sample 1999 to 2013, BEAM average returns decrease from 23.0%/yr by forming the portfolio on the first trading day of the month to 18.9%/yr by forming it on the third trading day of the month. The information ratio also declines from 1.61 to 1.15.

FIGURE 18

BEAM Performance for Different Trading Implementations

BEAM Performance Incorporating Shorting Costs and Trading Limits																	
		Execution Lag (EW)				Execution with Daily Stock Position Limit (EW with ADV constraint)									Max Capacity Strategy		
		0-day	1-day	2-day	3-day	5% ADV			10% ADV			15% ADV			(Position = 10% ADV)		
		Base-line				Day 1	Day 1&2	Day 1,2,&3	Day 1	Day 1 and 2	Day 1, 2, and 3	Day 1	Day 1 and 2	Day 1, 2, and 3	Day 1	Day 1 & 2	Day 1, 2, and 3
Original Sample (Jan. 1999 - Dec. 2013)	Avg Ret (%/Yr)	24.64	22.96	20.75	18.94	15.27	15.42	15.25	15.98	15.88	16.37	16.47	16.55	17.71	16.29	14.65	13.62
	Vol. (%/Yr)	14.58	14.30	15.18	16.43	19.58	17.82	17.63	17.77	16.42	16.06	16.75	15.89	15.43	22.34	22.30	22.77
	Inf. Ratio (Ann.)	**1.69**	**1.61**	**1.37**	**1.15**	**0.78**	**0.87**	**0.87**	**0.90**	**0.97**	**1.02**	**0.98**	**1.04**	**1.15**	**0.73**	**0.66**	**0.60**
	Worst Month Ret (%/m)	-16.59	-12.72	-17.24	-22.54	-20.92	-17.89	-19.58	-17.60	-16.01	-17.19	-15.99	-17.20	-15.21	-27.52	-28.62	-30.95
	Max Drawdown (%)	-16.59	-12.92	-24.72	-30.91	-37.49	-33.03	-30.57	-33.68	-28.39	-25.79	-31.08	-22.90	-21.65	-39.70	-36.92	-34.75
	Avg. Portfolio Capacity (in $MM, min of Long/Short Leg each month)														$264	$528	$791
Since Launch (Jan. 2014 - May 2018)	Avg Ret (%/Yr)	12.70	13.37	12.69	11.85	11.51	11.30	11.19	11.30	10.69	12.01	11.09	11.31	12.45	13.08	12.19	11.33
	Vol. (%/Yr)	11.63	11.75	11.81	12.48	12.03	11.65	11.54	11.52	11.80	11.58	11.44	11.54	11.66	15.70	15.55	15.50
	Inf. Ratio (Ann.)	**1.09**	**1.14**	**1.07**	**0.95**	**0.96**	**0.97**	**0.97**	**0.98**	**0.91**	**1.04**	**0.97**	**0.98**	**1.07**	**0.83**	**0.78**	**0.73**
	Worst Month Ret (%/m)	-5.69	-5.10	-5.13	-8.36	-6.97	-5.72	-5.72	-6.25	-5.79	-5.36	-5.99	-5.16	-5.11	-9.30	-9.93	-9.67
	Max Drawdown (%)	-10.28	-7.77	-7.30	-9.02	-12.51	-12.33	-11.98	-12.16	-14.64	-11.39	-12.69	-11.62	-11.10	-17.45	-17.04	-16.03
	Avg. Portfolio Capacity (in $MM, min of Long/Short Leg each month)														$516	$1,032	$1,548

Note: Prices assume VWAP execution between 10am and 12pm and are calculated based on a combination of open and close prices (0.42*open + 0.58*close, with the weights determined by cross-sectional regression of VWAP prices between (10am,12pm). We apply shorting cost of about 100bps/yr as suggested by the existing literature (e.g., Henderson et al., 2017; Drechsler and Drechsler, 2017, and references therein). The portfolio size is assumed to be $100mn.

Source: Compustat, Bloomberg, Barclays Research

Next we consider the price impact consequences by looking at the performance of BEAM portfolio after imposing the ADV 10% constraint. Deviating from EW to weighting by 10% ADV reduces performance. However, spreading the trades over multiple days brings the weights closer to EW and reduces the "shadow" cost of the ADV constraint, thus improving performance. The introduction of ADV constraints gives rise to a trade-off. On the one side, forming the portfolio earlier is better than later, as it avoids the decay of the value of the BEAM signal. On the other side, executing transactions over multiple days allows the weights to be closer to equal-weighting, which has better signal efficacy. This tension produces interesting results. For instance, in the sample 1999-2013, BEAM average returns decrease from 23% (baseline case in the second column) to 16% after imposing the 10% ADV constraint. By allowing a three-day implementation, and thus relaxing the ADV constraint, the average returns increase to 16.4%. Similar results are obtained for the recent period 2014 – 2018.

The columns "Max Capacity Strategy" show that BEAM capacity has increased substantially over the years. For the one-day implementation, the capacity was $264mn for the period 1999-2013, and has become $516mn for the recent period 2014-2018. The maximum capacity of the strategy since 2014 varied between $0.5bn and $1.5bn for one and three days rebalancing (assuming 10% ADV). Over the past two years the $0.5bn increased to $0.75bn. This increase in BEAM market capacity can be ascribed to two reasons. First, the overall stock market size is larger in recent years due to economic growth and inflation. Second, our bond-to-equity mapping has higher coverage ratio in recent years (see, e.g., Ben Dor, Guan and Rosa, *2018*, for up-to-date figures).

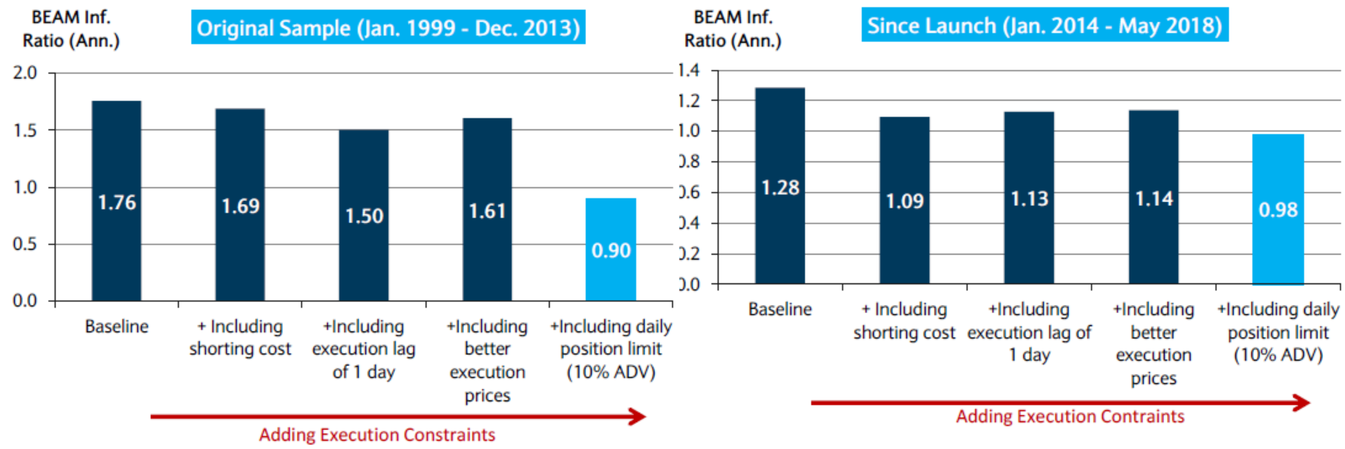
To shed further light on the impact of trading costs and execution constraints on portfolio performance, we look at the information ratio of five BEAM strategies, where trading constraints are sequentially imposed. First, as a benchmark, we start with the baseline BEAM portfolio (i.e., close-to-close returns based on the last trading day of each month). Second, we add shorting costs. Third, we include an execution lag of one trading day (close-to-close returns based on the first trading day of next month) Fourth, we relax the execution constraint by considering better execution prices. Specifically, we use the morning, as opposed to close, prices. Fifth, we include the costs associated to the price impact by including a daily position limit of 10% ADV. Figure 19 summarizes the results for two sample periods: original sample 1999-2013 (left) and post-publication sample 2014-2018 (right).

For the original sample period, including shorting costs reduces the annualized information ratio from 1.76 to 1.69. Imposing an execution lag of one full day further decreases the information ratio to 1.5. In other words, the decay of the signal of one day corresponds to a decrease in the information ratio of about 0.2. As the BEAM signal is generated the night of the last day of the month, it is possible to trade in the morning of the first trading day of the month, rather than at market close. By doing so, the information ratio increases to 1.61 from 1.5. When the constraint of daily position limit of 10% ADV is imposed, the information ratio decreases to 0.9. In sum, trading costs reduce BEAM information ratio to 0.9 from 1.76 for the sample period 1999-2013.

We look at the impact of trading costs for the more recent (post-publication) period, and the results are reported in Figure 19 (right). We find that trading costs and execution constraints reduce the information ratio to 0.98 from 1.28, with a pattern that is remarkably similar to the in-sample period. The main difference is that in the out-of-sample period the baseline BEAM information ratio is 1.28 compared with 1.76 for the original sample. This decline does not reflect a weakening of the signal but rather can be attributed to a low-volatility environment since 2014, together with the fact that BEAM performs exceptionally well in "bad" states (cf. Figure 9). Despite the lower gross-of-transaction-costs performance, the net performance is very similar, because the transaction costs have declined, especially the cost of the daily position limit constraint. For the period 1999-2013, the 10% ADV constraint reduces the information ratio to 0.9 from 1.61, while for the more recent period 2014-2018 the information ratio declines to 0.98 from 1.14. As we discuss above, this is the consequence of both an increase of stock market size and a better coverage of our QPS mapping algorithm.

FIGURE 19

BEAM Information Ratio with Execution Constraints



Note: The first three bars in each figure were BEAM traded at close. '+including better execution prices' were traded at morning prices, approximated by 0.42*open + 0.58*close with the weights determined by cross-sectional regression of VWAP prices between (10am,12pm) of BEAM universe on open and close prices that day. '+including daily stock limit (10% ADV) assumed portfolio size of $100mn. We use shorting cost of about 100bps/yr as suggested by the existing literature (e.g., Henderson et al., 2017; Drechsler and Drechsler, 2017, and references therein).

Source: Compustat, Bloomberg, Barclays Research

BEAM performance is robust to taking into account price impact and shorting costs. An important consideration to keep in mind is that BEAM performance reported in Figure 18 and Figure 19 should be interpreted as a lower bound on the actual performance figures, as we do not attempt to optimize the BEAM portfolio construction for trading costs or to develop an execution algorithm that depends on the economic environment. For instance, in terms of optimization, we could have implemented the BEAM portfolio by finding the solution that maximizes after-trading cost returns subject to maintaining the factor exposure of the original BEAM portfolio, similar to what Frazzini, Israel and Moskowitz (2012) have done. By doing so, and taking into account the execution algorithms of a large and sophisticated trader, the real-world trading costs and price impact function will be about an order of magnitude smaller compared with what we reported.

BEAM Extensions: Across Geographies, at High-Frequency, and for Sector Timing

BEAM across Markets: European Evidence

The BEAM portfolio has generated an annualized return of 23% and an information ratio of 1.66 (cf. Figure 4). Its performance has been consistent over time and by market states. All this evidence is, however, based on the U.S. stock market. To what extent the BEAM signal is effective in other markets? This question is important as factors should be robust across geographies (Asness, Moskowitz and Pedersen, 2013, Fama and French, 2012, Beck, Hsu, Kalesnik and Kostka, 2016). Furthermore, from an investor's standpoint, if the BEAM signal works internationally, the breadth of the strategy will be broader. Ben Dor, Guan and Zeng (*2018*) extend the BEAM study by looking at the relationship between corporate bond performance and subsequent equity returns in European markets.

To incorporate bond-level information in the construction of equity portfolios, it is necessary to observe a firm's capital structure, and in particular to match the equity and bond data of the same firm. As we discussed in the Introduction, this matching task presents a number of challenges, such as the absence of a common firm-level identifiers across the equity and bond markets and the presence of corporate actions with different consequences on bonds and equities. Linking bonds to equities is even more challenging for European firms compared with U.S. companies. First, European security data are usually of lower quality compared with the U.S. data as research on European markets generally receives less attention. Second, European markets are essentially a collection of individual markets from many different countries, which means some security identifiers that are unique within one country may not be unique across countries. The cross border universe also implies other complexities such as cross-listings and different currency denomination. To establish the link between the bond and equity databases, Ben Dor, Guan and Zeng (*2018*) use the linking table developed by Barclays' Quantitative Portfolio Strategy group, as there is no such historical linking table commercially available.

Similar to the U.S., incorporating information from bond prices enhances the traditional equity momentum strategy also in Europe. The monthly BEAM portfolio delivers an annualized information ratio of 0.74 for the period between 2003 and 2017, whereas the traditional equity momentum portfolio generates an information ratio of 0.26 over the same period and with the same set of equities.

Ben Dor, Guan and Zeng (*2018*) not only examine the profitability of the BEAM strategy in Europe, but also explore whether the BEAM signal dynamics documented in the U.S. carries over to Europe. Of note, the European evidence represents a true out-of-sample test based on fresh new data. Figure 20 shows side-by-side several portfolio formation specifications for the U.S. (left) and Europe (right). Specifically, it reports the performance of bond-ranked momentum portfolios by ranking period (in columns), and whether the most recent month is excluded (top panel) or included (bottom panel) in the ranking window.

The key finding of Figure 20 is that the BEAM signal has the same dynamics in European markets as it has in the U.S. In both regions, the effectiveness of the bond signals decays over time as the ranking window increases to 12 months from three months. As a corollary, the best performance, in terms of returns, volatility and information ratio, is for a ranking window of three months. In other words, the most salient information is contained in the months immediately preceding the portfolio formation date. Also in Europe, the BEAM performance is better by including in the ranking window the most recent month.

FIGURE 20

Performance of Bond-ranked Momentum Portfolios by Ranking Period (Top-Bottom Decile)

	U.S. (Original Paper)				Europe			
Ranking Window (Past k months)	k=3	6	9	12	k=3	6	9	12
				Panel A: Excluding Month t-1				
Avg (%/Yr)	12.21	12.90	7.57	6.18	7.64	7.07	5.38	6.94
Vol. (%/Yr)	15.40	18.09	18.39	19.68	12.81	16.67	15.98	16.64
Inf. Ratio (Ann.)	0.79	0.71	0.41	0.31	0.60	0.42	0.34	0.42
				Panel B: Including Month t-1				
Avg (%/Yr)	**17.38**	15.69	12.09	9.75	**11.40**	11.03	5.81	7.72
Vol. (%/Yr)	**14.97**	17.13	18.09	20.09	**15.36**	17.40	17.20	17.71
Inf. Ratio (Ann.)	**1.16**	0.92	0.67	0.49	**0.74**	0.63	0.34	0.44

Source: The sample period is January 1994 to December 2013 for the original paper, and May 2003 to December 2017 for Europe. The U.S. results are from Ben Dor and Xu (2014) and the European results are from Ben Dor, Guan and Zeng (2018).
Source: Compustat, Bloomberg, Barclays Research

Ben Dor, Guan and Zeng (*2018*) show that a number of additional results carry over from U.S. to Europe. Stocks with top ranked past bond performance share similar characteristics (e.g., leverage, book-to-market ratio and beta to the overall STOXX Europe 600 index) with stocks with bottom ranked past bond performance, thus providing strong hedging abilities. In fact, the volatility of the long-short BEAM portfolio is about 60% the volatility of the long or short portfolio. In contrast, the volatility of the long-short equity momentum portfolio is roughly the same as the volatility of the long- or short-side.

In line with what documented in the U.S., the European BEAM is not an industry bet. Removing industry-level momentum does not affect BEAM performance. Furthermore, the long-short BEAM portfolio outperforms equity Momentum not only on average, but also in different market conditions, especially during the financial crisis. In 2008-09 European BEAM average annualized returns were 20%, while momentum returns were -22%. The main reason why BEAM has outperformed Momentum in market reversal is that BEAM has a beta with the stock market of about zero, both on average and during the financial crisis. In contrast, the correlation between equity Momentum and the overall European stock market becomes negative during the financial crisis. When the overall market bounces back, the beta behaviour results in large losses, as winner stocks have low beta and loser stocks feature high beta.

When applied to European markets, the BEAM portfolio has delivered positive and stable long-term returns, with low correlation to other international risk factors. More importantly, we find BEAM portfolio's performance dynamics feature the same dynamics in European markets as it has in the U.S.

BEAM and High-Frequency Trading: D-BEAM

Ben Dor, Guan and Rosa (*2018*) extend Ben Dor and Xu (*2014*) analysis by using daily, as opposed to monthly, credit signals to form high-frequency equity Momentum portfolios, so called Daily-BEAM (in short, D-BEAM). This extension is important for two reasons. First, the development of a daily signal is useful for high-frequency investors in systematic equity strategies. Second, if the daily strategy proves profitable, it corroborates the idea that bond prices provides valuable information for equity investors.[8] Corporate bonds are relatively less liquid compared with equities, especially at daily frequency. In particular, corporate bonds trade over-the-counter and most of their trading volume tends to occur during the first few days after the bond is issued. Therefore, a key requirement for implementing D-BEAM is the availability of a high-quality, easily accessible and comprehensive *daily* corporate bond pricing dataset. Another important consideration is the availability of a reliable linking table between the bond identifier (at the security level) and its parent company.

The use of daily bond signals has generated average annualized returns of more than 18% and an information ratio of 1.8 since the start of the sample in 2001.[9] Moreover, D-BEAM has generated positive returns in all years but one, and steady performance in different economic states, such as in high or low interest rate environments or in both expansions and recessions.

A key contribution of Ben Dor, Guan and Rosa (*2018*) study is to show that all the BEAM signal and performance dynamics documented for lower-frequency bond signals continue to hold for higher-frequency data. D-BEAM remains a momentum strategy, where past winners are bought and past losers are sold. This result is in stark contrast to the findings based on equity signals. Whereas equity prices are characterized by momentum over the intermediate term of three to 12 months (Jegadeesh and Titman, 1993), stock prices reverse over the shorter run (see Jegadeesh, 1990, for more details). Put differently, BEAM is always a momentum signal irrespective of the strategy frequency, while equities feature mean

[8] In a recent paper, Mao (2012) uses *intraday* data to show that corporate bond markets contribute more than 10% to price discovery in equities. To measure price discovery, the author uses the information share approach developed by Hasbrouck (1995), which, in contrast to a Granger causality test, only considers permanent changes of prices and ignores transient price of disturbances.

[9] The main analysis is based on a conservative assumption that the BEAM signal (using data up to day t-1) is delivered during day t and returns are therefore computed from the close on day t to the close on day t+1. The D-BEAM signal becomes available before the stock market open. The information ratio increases to over 2.5 if the trades are executed on the open of the following day as opposed to the close.

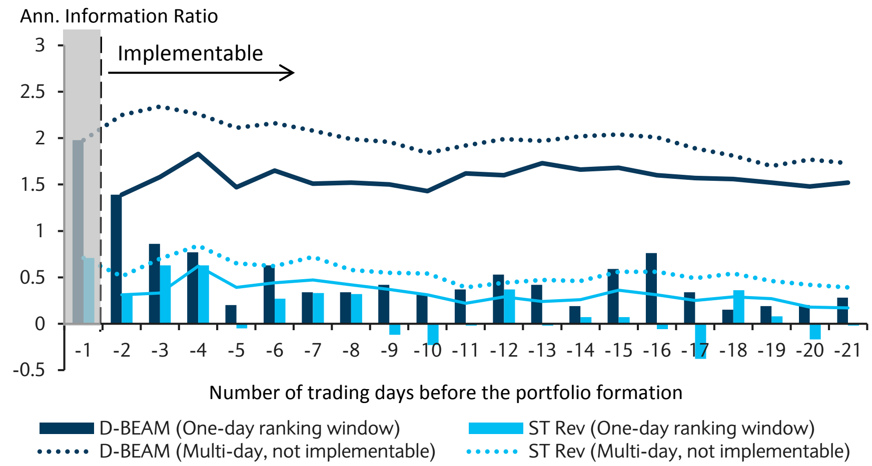
reversion at higher frequency and a contrarian strategy (i.e., past losing stocks outperform past winning stocks) is profitable.

The most relevant information is contained in the days immediately preceding the portfolio formation. To highlight the additional informational content contained in each trading day included in the ranking window, we analyze the performance of portfolios based on a one-day ranking window for D-BEAM or short-term reversal strategies. Figure 21 displays the average annualized return of strategies based on ranking windows of only one day (bar chart) or based on information cumulated over multiple days (line charts). We also look at the information content of the last day prior to portfolio formation, both in isolation (i.e., the bar associated to "-1") and as part of a multiple-day ranking window (dotted lines). The vertical dashed line indicates what strategies are implementable, and is based on the conservative assumption of skipping one trading day between signal construction and portfolio formation. In contrast, the shaded area indicates that strategies based on the day immediately preceding the portfolio formation may not be implementable. To clarify the notation, the signal associated to the dark blue bar at "-4" corresponds to the bond excess returns between the trading day t-5 and t-4, whereas the light blue bar corresponds to the short-term reversal strategy, and is based on total equity returns between day t-5 and t-4. In both cases, the returns of the equity portfolio are computed from the close on day t to the close on day t+1. The solid dark blue line associated to "-4" represents the average return of the D-BEAM strategy based on the formation window between -4 and -1, and with one day holding period between day 0 and +1.

Figure 21 shows that a D-BEAM strategy that relies on a multiple-day ranking window generates higher information ratios than those generated by a D-BEAM strategy that relies only on a ranking window of only one day. Specifically, the lines always lie above the bar charts. Most of the valuable information is contained in the days immediately preceding the portfolio formation. On the one side, the height of the bars declines the farther in the past is the construction window compared with formation date. On the other side, the lines, which represent the average returns from multiple-day ranking windows, are positively sloped for the first four days, and then they flatten out thereafter. Of note, the day immediately before the formation date contains valuable information, producing an average return of 18% and an information ratio of 2. Moreover, the dotted lines are always above the solid lines. For instance, the D-BEAM performance based on the four most recent ranking days produces an annualized information ratio of 2.26 compared with an information ratio of 1.83 using a three-day ranking window from t-4 to t-1. These findings are in line with the results discussed in *Ben Dor and Xu (2014)* for the monthly BEAM strategy. In that case, the inclusion of the most recent month results in a significant performance improvement, irrespective of the ranking window or weighting scheme. Finally, the results for short-term reversals are similar with those of D-BEAM. Most of the signal information is contained in the trading days immediately preceding the portfolio formation.

FIGURE 21

Information Ratio of Bond and Equity Signals by Ranking Window (one- vs. multi-day)



Note: The sample period is January 2001 to December 2017. This figure plots the annualized information ratio for equally weighted D-BEAM and short-term reversal portfolios ranked within industries, and based on decile portfolios. The bar chart displays the annualized information ratio of strategies based on ranking windows of one day, while the lines are based on information cumulated over multiple days (from one to 21 days prior to the portfolio formation). The shaded area indicates that the strategy may not be implementable, and is reported only for information purposes.
Source: Compustat, Bloomberg, Barclays Research

Consistent with prior (monthly) results, D-BEAM long-short (L/S) portfolio has always lower volatility than equity short-term reversal. In addition, for the daily signal, the volatility of the top and bottom bond-ranked decile portfolios is similar, but the combination of top and bottom deciles in a long-short portfolio results in about half the volatility than each portfolio. This finding suggests that top and bottom bond-ranked deciles hedge each other effectively, and reflect the tendency of the bond signal to generate long and short portfolios with similar factor exposures. We also find that ranking within industries leads to better performance compared with ranking across industries. The industry-neutral D-BEAM generates similar returns compared with ranking across industries, but displays lower volatility, hence resulting in an improvement in the information ratio by about 60%, from 1.17 to 1.83. This finding shows that D-BEAM is not driven by sector effects.

Since corporate bonds are relatively less liquid compared with equities, Ben Dor, Guan and Rosa (*2018*) investigate whether the efficacy of the bond signal is affected by the liquidity of the underlying bond. To do so, the authors rely on bond-level liquidity measures developed by Barclays' Quantitative Portfolio Strategies Group, such as Liquidity Cost Scores (LCS) and Trade Efficiency Scores (*Konstantinovsky, Ng and Phelps, 2015*). They find that D-BEAM performance monotonically increases with the liquidity of the underlying bonds.

BEAM for Sector Timing

We have explored BEAM performance across geographies and at different frequency. In this section we investigate whether the BEAM signal can be helpful for sector timing. Conceptually, this exercise is interesting because it boils down to test the efficacy of BEAM to a different level of aggregation compared with what we have documented at the security level.

The sector rotation strategy comprises two steps. First, we construct sector-level BEAM signals by combining (value-weighting) individual stock's BEAM signals at the sector-level (based on the first 2-digit GICS code).[10] As a benchmark, we also construct sector-level

[10] As a robustness check, we also consider an alternative construction method that consists of computing sector-level BEAM signals from past sector-level bond excess returns. The performance results (available upon request) remain qualitatively similar to those reported in Figure 22.

equity momentum signals. The ranking period for BEAM is a three-month window, while the ranking period for momentum is a 12-month window, skipping the most recent month. The stock universe comprises stocks that are in the based on the Russell 1000 index. Second, each month, Top 5 and Bottom 5 sectors ranked on BEAM (or equity momentum) are grouped to form two equally weighted portfolios. We aggregate multiple sectors to reduce noise from an individual sector.

Figure 22 reports the performance results for BEAM and equity momentum, and the S&P500 and Russell 1000 Index as additional benchmarks for the sample period January 1999 to May 2018. BEAM Top 5-sector portfolio outperforms the Bottom 5-sector portfolio by 3.49% per year. The Momentum Top 5-Bottom 5 outperformance is much weaker, at 1.53% per year. The volatility of the BEAM portfolio is also lower than the volatility of the momentum portfolio, and thus the BEAM Information ratio is about three times as large as the momentum information ratio (0.39 versus 0.12). The BEAM Top 5-Bottom 5 portfolio has smaller worst month loss and maximum drawdown than Momentum Top 5-bottom 5 portfolios. The trailing 12-month BEAM portfolio returns are positive more frequently than the momentum returns (67% vs. 53%).

FIGURE 22

Performance of Top 5 Sector – Bottom 5 Sector

	BEAM			Momentum			S&P 500 Index	Russell 1000 Index
	Top 5	Bottom 5	Top-Bottom	Top 5	Bottom 5	Top-Bottom		
Avg Ret (%/Yr)	10.03	6.54	**3.49**	9.08	7.72	**1.35**	7.03	7.35
Vol. (%/Yr)	14.41	14.58	**9.04**	14.33	15.91	**11.73**	14.40	14.59
Sharpe (Inf.) Ratio (Ann.)	0.55	0.30	**0.39**	0.48	0.35	**0.12**	0.34	0.36
Worst Monthly Ret (%/m)	-16.59	-16.65	**-10.65**	-15.35	-20.50	**-14.47**	-16.79	-17.46
Max. Drawdown (%)	-46.46	-51.70	**-20.29**	-45.87	-55.94	**-21.36**	-50.95	-51.13
Correlation with S&P 500 Index	0.89	0.94	**-0.10**	0.90	0.90	**-0.12**	1.00	1.00
% (Trailing 12m Ret>=0)	82%	74%	**67%**	79%	77%	**53%**	77%	76%

Note: The sample period is January 1999 to May 2018. The sample comprises all issuers that are part of the Bloomberg Barclays corporate or High Yield indices and are included in the Russell 1000 Index. Portfolio sector returns contain all Russell 1000 constituents, not only limited to stocks with BEAM signals. The sector definition corresponds to the GICS first 2-digit sector. BEAM is based on a three-month ranking window and Momentum on a 12-month ranking window skipping the most recent month. All returns are based on equally weighted portfolios. Each month the top 5 sectors are bought and the Bottom 5 sectors are sold.
Source: Compustat, Bloomberg, Barclays Research

Conclusions

In a seminal paper, Ben Dor and Xu (2014) documents that credit signals enhance equity momentum strategies. Specifically, a U.S. equity momentum portfolio that ranks stocks by past excess returns of bonds issued by the same company outperforms the traditional momentum portfolio based on past stock returns. This paper shows that the BEAM strategy has continued to deliver strong positive returns since the publication of the original BEAM study in 2014. In the out-of-sample period average returns are 18.5% and its information ratio is 0.85 compared with 17.4% and 1.16 in the in-sample period. Furthermore, we document that BEAM performance has been consistent along several dimensions, including across industries, over time and by market states.

BEAM signal has proven to be valuable not only in isolation, but also in a portfolio setting. We show that BEAM is not spanned by exposures to commonly used asset pricing factors, and it generates significant alpha relative to those factors. Hence, an investor already trading the Fama and French factors could realize significant gains in an ex-post mean variance efficient portfolio setting by starting to trade BEAM. Importantly, BEAM performance is robust to trading costs and capacity limits.

Since 2014, we have continued to carry out research on BEAM by expanding its coverage along several dimensions, such as across geographies (in European markets), frequency (at daily as opposed to monthly frequency), and at different level of signal aggregation (for sector timing purposes). More generally, we have leveraged our long history and expertise in quantitative credit research, the access to a rich global database on corporate bond prices and analytics, and our unique mapping algorithm to further explore the interactions between credit signals and systematic equity strategies. For instance, Ben Dor, Guan, Kishore, Rosa and Zeng (*2018*) look at the bond price reaction to earnings announcement. They find that it has predictive power for post-announcement stock returns and that it is incremental to the information embedded in earnings surprises or earning announcement return. Ben Dor and Guan (*2016*) investigate whether 'value', as opposed to momentum (as in BEAM spillover across asset classes). They show that a measure of 'value' in credit, similar to Shiller's CAPE generates significantly better information ratios compared with those of equity value strategies, such as Book-to-Market or Price-Earnings. Finally, Ben Dor and Guan (*2018*) investigate the 'low vol.' phenomenon (i.e., the tendency of lower-risk assets to outperform high-risk assets on a risk-adjusted basis) across asset classes, focusing on HY bonds vs. equities. They document that the 'low vol.' Anomaly is also present across asset classes with HY bonds that have higher Sharpe ratios than equities of the same company. To conclude, we have documented that the value of credit signals in equity strategies is robust and pervasive, and it is currently an active area of ongoing research.

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