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BEAM (Bonds in Equity Asset Momentum)

Introducing D-BEAM: Daily Equity Momentum Strategy Based on High-Frequency Credit Signals

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- **Ben Dor and Xu (2015) analyze whether the information contained in corporate bond returns can be used to construct equity portfolios. They document that a monthly Bonds in Equity Asset Momentum (BEAM) strategy, which buys stocks the corresponding bonds of which outperformed relative to peers and sells short stocks the corresponding bonds of which underperformed relative to peers, produces an improved risk-return profile compared with a standard equity momentum strategy.**
- **This paper extends Ben Dor and Xu's analysis by using daily bond signals to form a high-frequency equity momentum strategy.**
- **Unlike equity returns, which exhibit short-term mean reversion, daily bond returns are associated with momentum in equities and can be used to form a daily trading strategy (D-BEAM).**
- **The D-BEAM strategy has generated an annual average return of 18% and an information ratio of 1.8 starting in 2001, with positive returns in all years but one.**
- **The D-BEAM signal is valuable both in isolation and when combined with other strategies, generating significant risk-adjusted alpha after controlling for commonly used equity factors. Hence, D-BEAM provides considerable diversification benefits.**
- **We investigate to what extent the efficacy of the bond return signal depends on the liquidity of the underlying bonds. Using novel measures of corporate bond liquidity, we document that D-BEAM average performance is always positive across different buckets sorted on the liquidity of the underlying bonds.**
- **The D-BEAM strategy has continued to deliver strong positive returns over time (i.e., since the publication of *our presentation* in early 2018) and across geographies (i.e., in *European markets*). These results provide additional out-of-sample validation of our original U.S. D-BEAM findings, and confirm the value of using credit signals in high-frequency systematic equity strategies.**

Introduction

Momentum strategies have delivered large positive and significant returns across multiple time periods, equity markets, and asset classes.[1] A momentum strategy of buying past winners and selling past losers produces positive returns in U.S. equities (Jegadeesh and Titman, 1993). Despite the extensive momentum-related research within a given asset class, the efficacy of cross-market momentum strategies has received little attention.

The idea of using price information from the corporate bond market in the construction of equity portfolios is intuitively appealing, and provides an ideal setting to study momentum spillovers from one asset class to another. For instance, Merton (1974) outlines the link between stocks and bonds, and illustrates that both assets represent different claims to the same underlying operating cash flows and are affected by the same firm fundamentals.[2] There are, however, several reasons why the information reflected in the pricing of bonds and stocks issued by the same company may not be the same. First, the corporate bond and equity market are segmented, featuring a different investor base, and possibly resulting in different information sets. Second, the pricing models of debt and equity securities differ. Corporate bonds are typically priced more quantitatively than stocks, and their valuations tend to be less subject to investors' behavioural biases, and thus less likely to under-react or over-react to news. Third, as trading bonds is typically more costly than equities, investors may trade bonds in the secondary market only if the value of their information exceeds the marginal cost of trading. Changes in bond prices, therefore, are more likely to reflect real information rather than noise compared with equity prices.

Although the U.S. corporate bond market is enormous, with outstanding principal larger than $9.3 trillion in Q1 2019 (source: *SIFMA*), corporate bonds trade over-the-counter, trade less frequently and are less liquid than equities. For all these reasons, a key challenge in using credit signals in systematic equity strategies is the lack of a high-quality, easily accessible and comprehensive corporate bond pricing dataset, unlike those datasets available for equities. In a seminal paper, Ben Dor and Xu (2015) introduced the idea of employing credit signals in systematic equity strategies. They document that a monthly Bonds in Equity Asset Momentum (in short, BEAM) strategy, which goes long stocks the corresponding bonds of which outperformed relative to peers and shorts stocks the corresponding bonds of which underperformed relative to peers, produces an improved risk-return profile (i.e., higher average returns and lower volatility and tail risk measures) compared with a standard equity momentum strategy. Two recent contributions have confirmed Ben Dor and Xu's (2015) insight that related securities linked through firm fundamentals provide important cross-market return performance information. Murfin and Addoum (2018) look at private, instead of public, debt, and they document momentum spillovers from syndicated loans to equities of the same companies. Lee, Naranjo and Sirmans (2018) document positive momentum spillover from the CDS market to equity portfolios, with most of the performance concentrated in junk grade companies.

This paper extends the analysis of Ben Dor and Xu (2015) by using high-frequency (daily) credit signals to construct equity portfolios. Specifically, we develop a daily BEAM strategy, henceforth defined as D-BEAM, that buys stocks with high past bond returns and sells short stocks with low past bond returns. We find that the D-BEAM strategy generated an annualized average return of 18% for the period 2001-2017, with an information ratio of

[1] Among others, Moskowitz and Grinblatt (1999) document the efficacy of momentum strategies for U.S. industry portfolios, Rouwenhorst (1998 and 1999) for developed and emerging markets, Durham (2015) for U.S. Treasuries, Jostova, Nikolova, Philipov and Stahel (2013) for corporate bonds, Menkhoff, Sarno, Schmeling and Schrimpf (2012) for currencies, Erb and Harvey (2006) for commodities, Carhart (1997) for mutual funds chasing performance, and Asness, Moskowitz and Pedersen (2013) across assets.

[2] Schaefer and Strebulaev (2008) investigate empirically the implications of the Merton model and cannot reject the hypothesis that the model implied and empirical hedge ratios are equal.

1.8. Furthermore, in line with the monthly BEAM results, the D-BEAM performance improves in risk-adjusted terms when implemented in its industry-neutral hedging form. In particular, an "industry-neutral" D-BEAM portfolio, where stocks are ranked within industries rather than across the overall universe, generates a higher information ratio than the standard D-BEAM portfolio.

In the first part of the paper we describe the data and the equity universe. Then, we discuss the portfolio construction of bond-ranked daily momentum strategies, and evaluate their performance over various signal formation windows.

In the third part, we examine the efficacy of D-BEAM signals in detail from several dimensions. First, we dissect the risk-adjusted performance of the D-BEAM signals into two components: the large return difference between the long and the short legs; and the effective hedging of the long and the short legs that substantially reduces volatilities in the L-S portfolio. We find that the decile average returns are monotonically increasing in the signal strength of D-BEAM, and we also find that all D-BEAM deciles have similar return volatilities, but the long-short portfolio has markedly lower volatility than each leg. Next, we look at whether D-BEAM signals offer additional predictive power of future returns besides short-term reversal through a conditional double sort analysis on the bond and equity signals (past bond returns and past equity returns, respectively). We find that sorting on the bond signals generates higher information ratios within each equity signal bucket than vice versa, indicating that the bond signals have more additive value than the equity signals. In additional, since corporate bonds are relatively less liquid than equities, it may be of concern whether illiquid bonds provide any useful information for equities. We investigate to what extent the efficacy of the bond signals is affected by the liquidity of the underlying bonds. Using novel measures of corporate bond liquidity, such as Liquidity Cost Scores and Trade Efficiency Scores (Konstantinovsky, Ng and Phelps, 2016), we document that average D-BEAM performance was positive across all (low/medium/high) bond liquidity buckets. Hence, even in the least liquid segment of the corporate bond market, the D-BEAM signal remains effective.

A central investing tenet is that the value added of a strategy should not be considered in isolation, but rather in a portfolio setting when combined with other strategies. Hence, understanding how D-BEAM relates to other standard daily risk factors is as important as assessing the D-BEAM performance as a stand-alone strategy. We show that D-BEAM returns are uncorrelated with standard risk factors. Moreover, using a time series regression, we find that D-BEAM returns have very low factor loadings to standard risk factors, thus indicating that D-BEAM returns are not spanned by other asset pricing factors. We also document that D-BEAM has a large and significant risk-adjusted alpha, ranging between 18% and 22% per year, depending on the underlying risk model. Another way to examine the potential value of the D-BEAM strategy to investors is to consider the incremental performance that could be achieved in an ex-post mean-variance efficient portfolio. We find that the inclusion of D-BEAM to the investable set of the Fama-French three factors boosts the information ratio, more than tripling it from 0.60 to 1.99. All in all, these findings suggest that D-BEAM not only produces a large and significant alpha, but also adds considerable diversification benefits to a general portfolio with investments in the common risk factors.

In the last part of the paper, we look at the consistency of D-BEAM performance along several dimensions, including over calendar time (i.e., years, months and day of the week), across different economic states, in out-of-sample period, and in the European markets. D-BEAM performance was stable over time and did not vary much by the type of market environment. In contrast to equity momentum (e.g., Daniel and Moskowitz, 2016), D-BEAM did not experience crashes (i.e., infrequent, persistent and large strings of negative returns).

Out-of-sample performance is often viewed as the "gold standard" of evaluation of a theory. We introduced the D-BEAM strategy in Ben Dor, Guan and Rosa (*2018*) in April 2018. In our original study, the sample ended in December 2017, and we use the same case in the main analysis of this paper. Since then, we have accrued about one and a half year of live data to assess the out-of-sample performance of D-BEAM. Significantly, we find that D-BEAM performance has improved in the out-of-sample period relative to the back-testing, having an information ratio of around 3 since January 2018. This result is in stark contrast with out-of-sample evaluations of most strategies. Portfolio returns decline on average between 26% and 58% in the out-of-sample period (Mclean and Pontiff, 2016). One potential explanation of this stark contrast to other strategies is that the availability of the data underlying the construction of the D-BEAM portfolio. Unlike equities, where single-stock data go back to at least 1926, no such data are commercially obtainable for U.S. corporate bonds, especially at a daily frequency. The availability of a real-time security-level bond-to-equity mapping represents another significant bottleneck to prevent the use of bond prices for equity investing. These barriers to entry may have, in effect, prevented the decay of the D-BEAM performance after its discovery.

D-BEAM has shown consistent out-of-sample success not only over time, but also across geographies, such as in European markets, where D-BEAM generates average annual returns of 14% and an information ratio of 1.3. Even more importantly, the European D-BEAM dynamics are mostly consistent with U.S. D-BEAM. For instance, D-BEAM remains a momentum signal, featuring invariably lower volatility than equity short-term reversal strategies. This evidence provides an additional out-of-sample validation from other markets of our main findings.

The rest of the paper is organized as follows. We start by describing the data and the equity universe. Then, we discuss the portfolio construction of bond-ranked daily momentum strategies, and evaluate their performance over various signal formation windows. We proceed by dissecting the efficacy of the D-BEAM signal by looking at performance across deciles, overlay with other equity signals, and investigating the relationship between D-BEAM performance and the liquidity of the underlying bonds. Next, we explore D-BEAM diversification benefits by computing its risk-adjusted alpha and inspecting its factor loadings on standard risk factors. Finally, we examine the consistency of D-BEAM performance over time, by market states, in out-of-sample period (i.e., since January 2018) and across geographies (i.e., in European markets).

Data

Data Sources and Firm Coverage

Our analysis uses bond and equity daily data for the sample period between January 2001 and December 2017. Our sample of U.S. corporate bonds includes both investment-grade (IG) and high yield (HY) bonds, which are the constituents of the Bloomberg Barclays U.S. Investment Grade and High Yield Corporate Indexes, respectively. These two indexes represent the investable universe of U.S.-dollar-denominated IG and HY corporate bonds publicly issued in the U.S. domestic market. We use corporate bond daily returns and analytics (e.g., option adjusted spread) from Barclays and Bloomberg. Our sample of U.S. equities includes all issuers that are part of the Bloomberg Barclays U.S. IG and HY Corporate Indices, and have publicly traded common equity on a U.S. exchange. We use equity daily total returns from the Compustat North America database.

Unlike equities that trade on an exchange, bonds trade over-the-counter, and bids to buy and offers to sell a particular bond are not centralized. Hence, one major obstacle to carry out this cross-asset research is the lack of a high-quality, easily accessible and comprehensive corporate bond pricing dataset.[3] The corporate bond returns data set used in this paper is considerably more extensive than those used in previous studies in three dimensions: it includes high-frequency (daily) data; it covers a long calendar span (about 20 years); and it includes both high-quality pricing and analytics information with comprehensive coverage on the cross-section of corporate bonds (e.g., in December 2017, the IG and HY corporate bond index contained around 8,000 bonds).

Another important challenge in using credit signals in systematic equity strategies is establishing the link between bond issuers and equity issuers, as the bond and equity datasets use different company identifiers. A number of issues arise in matching firm-level identifiers across equities and bonds. Companies usually have a single class of common shares traded at any point in time, but may have multiple outstanding bonds and issues, with distinct maturity, seniority, rating and other structural differences (e.g., callability, convertibility, embedded protections, coupon rates, etc.). Moreover, corporate bonds might be issued by different subsidiaries, operating potentially in different industries, but that are all associated to the same parent company. On top of that, corporate actions may have different effects on the trading activities of bonds and equities. For instance, bonds issued by the acquired company often continue to trade after the acquisition, whereas equities cease to do so. The linking table should also take into consideration that stocks and bonds identifiers, such as CUSIPs, ISINs or tickers, may change over time. To tackle these challenges, we rely on the linking table developed by Ben Dor and Xu (2015). This mapping table provides the historical matching of corporate bonds issuers to Compustat data by combining multiple identifiers (e.g., Barclays' identifiers, CUSIPs, tickers, issuers' names, stock prices, etc.) and using data from multiple sources, such as Barclays fixed income and equity data, Bloomberg data and Compustat.

Figure 1 shows the number (left columns) and bond market value (right columns) of issuers with corporate bonds included in the Bloomberg Barclays U.S. IG and HY Corporate Index. Panel A reports the results for the IG Index, Panel B for the HY Index, and Panel C for the Aggregate Index (IG and HY). The results are shown for December 2001 and in four-year increments thereafter, until December 2017. "Index population" refers to the overall number of issuers present in the Index at a given point in time. "Mapped Issuers" represents the issuers that have been linked with equity information from Compustat. "Included in the sample" indicates those issuers included in our final sample.

The issuers included in the sample are a subset of the issuers in the Index population for a number of reasons. First, private companies are never assigned any of the equity identifiers used in the matching process, and hence are not included in the "Mapped Issuers" sample.[4] Second, we only consider issuers with common shares. Additionally, to prevent exchange rate dynamics from affecting the results, we exclude from our sample American Deposit Receipts (ADR).[5] Third, to mitigate the impact of microstructure effects associated with low priced stocks, we remove very small stocks (so-called "penny stocks") with an open price below $1 or a market capitalization below $50 million. In addition, to ensure that our sample contains relatively liquid stocks, we exclude OTC-traded stocks.

[3] To create better transparency into the bond market, the Financial Industry Regulatory Authority (FINRA), a self-regulatory body with jurisdiction over many over-the-counter bond dealers, has required that financial institutions report bond transactions to the Trade Reporting and Compliance Engine (TRACE) system. Our dataset is more comprehensive than TRACE for a number of reasons. First, it covers a longer time span (from 2001 rather than 2005). Second, it provides pricing and analytics information for all bonds in the Index and at the same point in time (market close) those prices are taken. Third, the pricing data do not suffer from market microstructure issues, such as bid-ask bounce, staleness, price discreteness, and clustering of prices.

[4] Public firms turned private are included in our sample as long the equity data remain available.

[5] To be precise, we apply two filters. First, the TPCI variable in Compustat equals 0 (i.e., common stock). Second, the IID variable in Compustat equals a number (i.e., IID < 20 implies no ADRs, and IID is a number eliminates international securities). We also use Compustat primary share class identifier to select the primary share classes (i.e., PRIMISS equals "P"). If the identifier is missing, we select the share class with the largest US dollar trading volume in the past month as the primary share class.

Panel A of Figure 1 shows that the number of issuers in the IG universe was roughly stable, ranging between 863 in 2005 and around 1,100 in both 2013 and 2017. In contrast, the total market capitalization all issuers increased more than threefold between 2001 and 2017, from $1.6 trillion to $5.2 trillion. The majority of IG issuers have been successfully mapped to companies in Compustat. The percentage ranges between 79% (of the Index population) at the start of the sample to 94%, in 2017 in terms of number of issuers, and between 88% in 2001 and 97% in 2017 in terms of bond market values. Because of our additional filters, such as the exclusion of ADRs, OTCs and micro caps, the number of bond issuers included in the sample is about 70% of the overall population in terms of number of issuers, and just under 80% in terms of market value.

Panel B of Figure 1 displays the success rates of the linking table over the years when applied to issuers comprising the HY Index. The success rate of the mapping algorithm is lower for HY than IG, around 60% based on number of issuers, and around 70% in terms of market value of the bonds. As discussed in Ben Dor and Xu (2015), the main reason for the lower matching rates is that many HY issuers are private firms, and as a result they do not have publicly traded stocks. Panel C of Figure 1 reports the matching rates for the combined IG and HY issuer population. The number of issuers included in the sample increases from 1,093 in 2001 to 1,452 at the end of 2017, representing respectively 94% (mapped issuers) and 76% (included in the sample) of the outstanding corporate debt issued by U.S. companies.

FIGURE 1

Matching of Bloomberg Barclays IG and HY Corporate Issuers to Compustat Equity Data

	Number of Issuers					Total Bond Market Value ($Bln)				
	2001	2005	2009	2013	2017	2001	2005	2009	2013	2017
Panel A: Corporate Index										
Index Population	1,173	863	902	1,089	1,088	1,586	1,609	2,488	3,718	5,174
Mapped Issuers	921	792	839	984	1,021	1,399	1,519	2,372	3,548	5,040
	79%	92%	93%	90%	94%	88%	94%	95%	95%	97%
Issuers Included in Sample	758	634	694	787	775	1,177	1,217	1,965	2,880	4,005
	65%	73%	77%	72%	71%	74%	76%	79%	77%	77%
Panel B: High-Yield Index										
Index Population	687	929	882	1,215	1,074	322	596	814	1,278	1,357
Mapped Issuers	400	550	547	662	770	244	462	565	819	1,109
	58%	59%	62%	54%	72%	76%	77%	69%	64%	82%
Issuers Included in Sample	335	463	486	576	677	221	382	524	703	952
	49%	50%	55%	47%	63%	69%	64%	64%	55%	70%
Panel C: Aggregate Universe (IG+HY)										
Index Population	1,860	1,792	1,784	2,304	2,162	1,908	2,205	3,302	4,996	6,531
Mapped Issuers	1,321	1,342	1,386	1,646	1,791	1,643	1,981	2,937	4,367	6,149
	71%	75%	78%	71%	83%	86%	90%	89%	87%	94%
Issuers Included in Sample	1,093	1,097	1,180	1,363	1,452	1,397	1,599	2,489	3,583	4,957
	59%	61%	66%	59%	67%	73%	73%	75%	72%	76%

Note: The figure illustrates the success of the matching table that links issuers with bonds included in the Bloomberg Barclays U.S. Investment Grade and High Yield indices to companies with publicly traded equities. The results are reported as of December of each year. The values shown in percentage terms represent the fraction of the overall population of the respective index. Source: Barclays Research, Bloomberg, Compustat.

Figure 2 provides additional information on the sample in terms of the number of stocks for the same five years (2001, 2005, 2009, 2013 and 2017) as in Figure 1. Panel A compares the firm coverage in our sample with the standard equity universe of stocks quoted on the NYSE, Amex or NASDAQ. This latter sample corresponds to companies present in the Center for Research in Securities Prices (CRSP) database that has been traditionally used in academic studies of factor investing.[6] Panel B looks at the coverage of the main equity indices, i.e., S&P 500, Russell 1000 and 2000, in terms of number of stocks and market capitalization.

Panel A indicates that the number of stocks included in our analysis increases from 644 in 2001 to 957 in 2013, and then levels off at 923 in 2017. The average market capitalization increased from $13 billion in 2001 to $25 billion in 2017, with a dip in 2009 due to the market crash during the financial crisis. In terms of number of companies, the standard equity universe featured a markedly different trend, with a steady decrease over time, from 5,501 in 2001 to 3,446 in 2017. An interesting aspect of Panel A is that the stock population was considerably smaller, between 60% and 70%, than the issuers population (reported in Figure 1). The reason is that in some cases different bond issuers are associated to the same equity issuers.

Panel B of Figure 2 zooms in on the coverage of key U.S. stock indices. Most of the constituents of the S&P 500 and Russell 1000 are included in the sample, with the coverage reaching around 85%-90% in terms of market capitalization toward the end of the sample period. The fact that the coverage in terms of market capitalization is higher than the coverage in terms of the number of companies suggests that our sample mainly consists of large cap companies. This finding is confirmed by comparing the coverage of the Russell 1000 with the Russell 2000 index, and indicates that the issuers of public debt are typically larger, more established companies.

FIGURE 2

Sample Coverage of Standard Equity Universe and Key Indices

		2001	2005	2009	2013	2017
Panel A: D-BEAM and Standard Equity Universe						
Sample	Number of Stocks	644	690	736	957	923
	Avg. Stock Size ($bln)	12.8	14.2	12.9	17.7	24.8
Standard Equity Universe	Number of Stocks	5,501	4,682	3,968	3,568	3,446
	Avg. Stock Size ($bln)	2.3	3.1	3.1	5.6	7.9
Ratio of Sample Agg. Market Cap to Standard Equity Universe		66%	67%	78%	84%	85%
Panel B: Coverage of Main Equity Indices						
S&P 500	Number of Stocks	62%	62%	69%	80%	79%
	Market Cap.	72%	75%	80%	86%	88%
Russell1000	Number of Stocks	43%	44%	50%	60%	60%
	Market Cap.	68%	68%	74%	80%	83%
Russell2000	Number of Stocks	8%	9%	9%	14%	12%
	Market Cap.	11%	12%	11%	20%	17%

Note: Panel A reports the number of stocks and average market value of each firm in the sample and in the standard equity universe. The number of constituents and average size (stock market capitalization) are available from Professor Kenneth French website. Panel B displays the percent of the population of main equity indices. The values shown in percentage terms represent the fraction of the overall population of the respective index. The results are reported as of December of each year. Source: Barclays Research, Bloomberg, Compustat, Kenneth French data library.

Short-Term Reversal Performance in Sample versus in the Standard Equity Universe

The results in Figure 2 indicate that our sample composition has a tilt to large-cap firms, and thus it is quite different than the standard equity universe usually used in the asset pricing literature to analyze factors performance in terms of coverage, size, and potentially other characteristics. Before proceeding with the analysis, we examine the extent to which

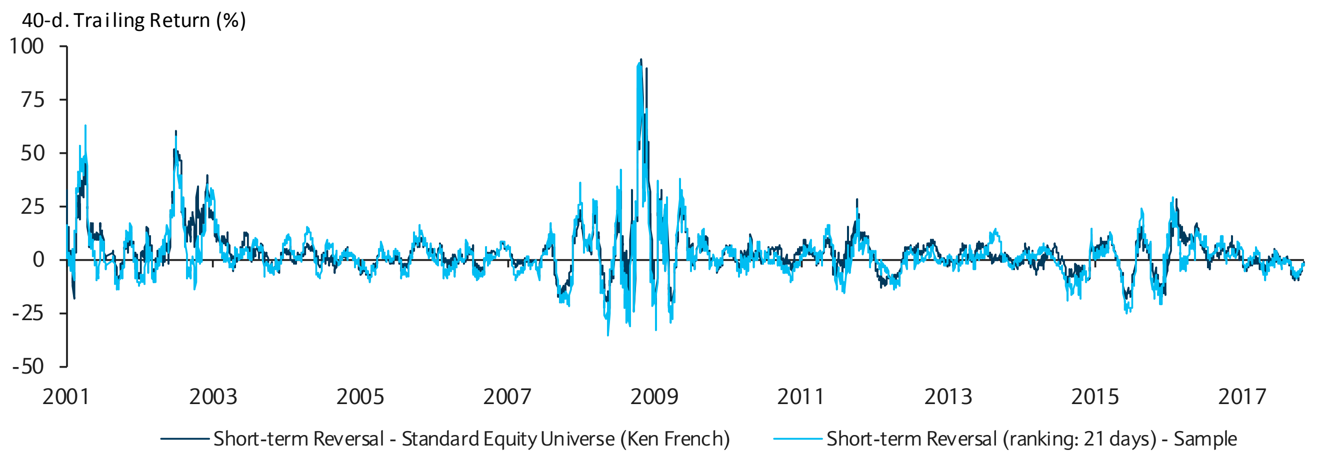
[6] The data on the standard equity universe are provided by Kenneth French data library. We thank Professor Ken French for making available a rich data library containing the time-series data for various risk portfolios (*http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ data_library.html)*, including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

our results are driven by the specific set of companies included in the study. To investigate this issue, we proceed in two steps. First, we define a benchmark equity strategy that we use to assess the sensitivity of the results to the universe selection. Second, we look at its return dynamics in our sample and in the standard equity universe (the stocks in the CRSP equity universe that are traded on NYSE, Amex or NASDAQ).

Equity prices are characterized by momentum over the intermediate term of three to twelve months (Jegadeesh and Titman, 1993). However, individual security returns tend to be negatively autocorrelated over shorter horizons (Lo and MacKinlay, 1990). Indeed, a short-term reversal strategy that sorts stocks into deciles on the basis of their prior-month returns, and then buys stocks in the bottom decile and sells stocks in the top decile, generates positive abnormal returns (Jegadeesh, 1990). For this reason, we use short-term reversal, rather than equity momentum strategy as our equity benchmark. Figure 3 displays the 40-day trailing cumulative returns of value-weighted short-term reversal based on our sample and on the standard US equity universe. Even though the number of stocks in our sample is far smaller than the number of stocks in the CRPS universe (around 4,000 stocks in December 2017) and comprises mostly large-cap companies, the two return series experience a similar pattern both in normal times and in volatile periods, such as during the financial crisis. Furthermore, the correlation of daily returns between those two short-term reversal strategies is roughly 90%. Overall, the results indicate that the return dynamics of short-term reversal strategy documented for the standard universe of firms in the U.S. were very similar in the sample used in this study. Hence, any potential differences in performance between short-term reversal and D-BEAM portfolios are not an artifact of our sample construction.

FIGURE 3

Short-Term Reversal in Sample vs. in the Standard Equity Universe



Note: The chart displays the 40-trading-day trailing cumulative returns of a short-term reversal strategy using the equity-bond-matched sample and the standard equity universe based on stocks traded on NYSE, AMEX and NASDAQ. The short-term reversal portfolio is formed by buying stocks in the bottom decile (past losers) and selling stocks in the top decile (past winners). Portfolios are rebalanced daily, and based on 21-day ranking window. Returns are value-weighted and ignore transaction costs. To make our short-term reversal strategy comparable to the short-term portfolios provided by Ken French data library, we consider the value-weighted version of the “10 Portfolios Formed on Short-Term Reversal”, daily frequency.

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

Bond-Ranked Daily Momentum Strategy: Portfolio Construction and Performance

Formation of the D-BEAM Portfolio

To form the D-BEAM portfolio, we proceed in three steps. First, we compute for each firm in the sample the daily aggregate excess returns of all its outstanding bonds (aggregated based on bond market capitalization). Second, we sort stocks into deciles on the basis of their prior k-day cumulative bond excess returns. Third, we form a portfolio by buying stocks in the top decile and selling stocks in the bottom decile, and compute its return for a holding period of one trading day.

In line with Ben Dor and Xu (2015), we use corporate bond returns in excess of duration-matched Treasury portfolios, instead of total returns, for several reasons. Excess returns are not affected by cross-sectional differences in bond durations among issuers when Treasury yields change. Other things equal, a short-maturity bond issued by one firm on average does not underperform a longer-maturity bond in terms of excess returns issued by another company in a month when Treasury yields fall. Moreover, excess returns measure only the component of return attributable to changes in the underlying fundamentals of the issuing firm. Finally, excess returns are not affected by cyclical trends in yields, though they incorporate different spread regimes.

To assess the informational content embedded in credit signals, we also construct long-short portfolios based on high-frequency stock return signals. As discussed above, a natural candidate is the so called short-term reversal strategy that forms portfolios by ranking stocks based on their prior k-day cumulative stock returns. Hence, consistent with the extant literature, we form portfolios and implement this strategy by buying the bottom decile (losers) and selling the top decile (winners). D-BEAM and short-term reversal strategies differ in two respects. First, the source of the information used in ranking stocks is different: respectively, bond and stock returns. Second, D-BEAM is a momentum strategy, i.e., buying past winners and selling past losers, whereas short-term reversal is a contrarian strategy, where past losing stocks outperform past winning stocks.

Figure 4 investigates the performance of D-BEAM and short-term reversal long-short portfolios along three dimensions: 1) length of the ranking window; 2) weighting scheme; 3) sorting methodology.[7] First, we consider five ranking windows, i.e., the length of the period over which past corporate bond and equity returns are cumulated. Second, we report results for two weighting schemes: equally weighted (EW) and value-weighted with a 2% cap (VW). The weighting scheme "VW" follows a value-weight rule based on market capitalization of the underlying stock, but limits the exposure of each stock to a maximum of 2% of the total value of the (decile) portfolio, with any excess weight redistributed on a pro rata basis across the remaining stocks within the decile. Third, we rank stocks across the whole universe (Panel A) or within industries (Panel B).[8] Previous research has shown that industry effects can play a key role in determining the performance of equity portfolios. For instance, Bali et al. (2006) examine industry effects on stock valuation and portfolio construction, and document that industry-neutral contrarian portfolios generate significantly positive returns. Liu et al. (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. Then we buy all top decile names (either ranked across the universe or within each industry) and sell short all bottom decile names to form the L-S portfolio using each signal.

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

[8] The industry classification for BEAM is based on the bond industry, whereas the classification for short-term reversal is based on the first two-digit GICS (Global Industry Classification Standard) codes.

FIGURE 4

Performance of D-BEAM and Short-Term Reversal L-S Portfolios by Ranking Windows, Weighting Schemes and across or within Industries

		Bond-ranked Momentum L-S Portfolios Buy Winners and Sell Losers					Short-term Reversal L-S Portfolios Buy Losers and Sell Winners				
Ranking Window (Past k days)		k=1	3	5	9	20	k=1	3	5	9	20
Panel A: Ranking across Universe											
EW	Avg. Ret. (%/Yr)	13.2	15.6	15.9	16.6	20.5	3.4	9.2	5.4	2.0	-1.0
	Vol. (%/Yr)	11.7	13.4	14.5	15.8	17.7	20.7	22.2	23.2	23.4	24.0
	Inf. Ratio (Ann.)	1.13	1.17	1.09	1.05	1.16	0.16	0.41	0.24	0.09	-0.04
VW	Avg. Ret. (%/Yr)	8.8	8.0	7.6	8.5	11.5	9.1	16.6	15.0	7.8	4.5
	Vol. (%/Yr)	11.5	13.5	14.6	15.6	17.4	21.4	22.8	23.9	24.3	25.1
	Inf. Ratio (Ann.)	0.80	0.60	0.50	0.50	0.70	0.40	0.70	0.60	0.30	0.20
Panel B: Ranking within Industries											
EW	Avg. Ret. (%/Yr)	12.7	18.2	17.1	15.6	18.0	4.5	9.8	7.3	5.2	3.0
	Vol. (%/Yr)	9.1	9.9	10.4	10.9	11.9	14.4	15.8	16.8	16.7	17.7
	Inf. Ratio (Ann.)	1.39	1.83	1.65	1.43	1.52	0.31	0.62	0.44	0.31	0.17
VW	Avg. Ret. (%/Yr)	8.90	10.5	9.8	8.0	9.6	7.9	13.5	12.7	8.5	6.5
	Vol. (%/Yr)	8.90	9.7	10.1	10.6	11.3	14.2	15.6	16.4	16.3	17.5
	Inf. Ratio (Ann.)	1.00	1.10	1.00	0.80	0.90	0.60	0.90	0.80	0.50	0.40

Note: The sample is from January 2001 to December 2017. "EW" stands for equally weighted and "VW" stands for value-weighted with a 2% cap, which relies on a value-weight rule based on market capitalization of the underlying stock, but limits the exposure of each stock to a maximum of 2% of the total value of the (decile) portfolio. Any excess weight is allocated on a pro rata basis across the remaining stocks within the decile. Returns and volatilities are calculated from the L-S portfolios (long top decile and short bottom decile or vice versa) for each signal specification and annualized by multiplying them respectively by 251 and $\sqrt{251}$. Portfolios are rebalanced daily, and returns ignore transaction costs. The information ratio is the ratio between average returns and volatility.
Source: Barclays Research, Bloomberg, Compustat.

Importantly, to make the strategies implementable, we leave a one-trading day gap between the day when the bond or equity returns are observed, and when the trades are executed to make sure that there are enough time between signal formation and transaction execution.[9] By skipping a day we also avoid various econometric problems, as short-term reversal strategies are plagued by market microstructure related frictions (e.g., bid-ask bounce, price pressure due to illiquid markets, non-synchronous data, etc.).

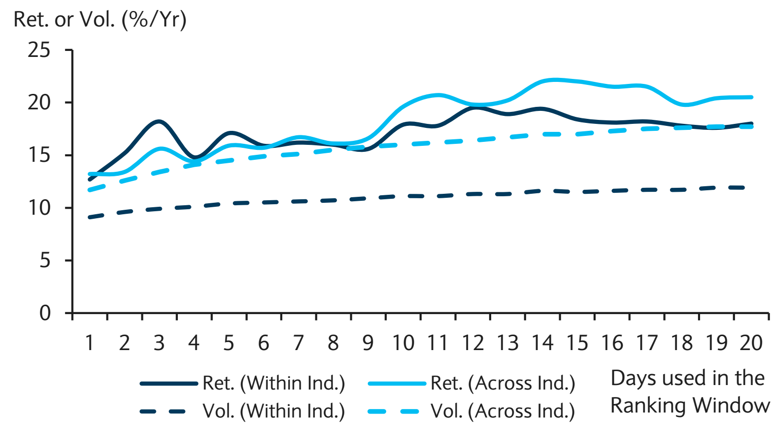
By inspecting Figure 4, three key findings emerge. First, most bond signals generate superior performance (higher returns and lower volatilities) compared with the portfolios based on equity signals. Second, the industry-neutral (i.e., ranked within industries) portfolios have higher information ratios than those portfolios constructed across industries. For instance, for the case of a three-day ranking window, the information ratio increases by roughly 60% for EW and 80% for VW. Third, unlike equities, bond-ranked signals show consistency in the direction of performance (e.g. past winners continued to be winners) and do not display price reversal patterns in the short-term as with the equity signals.

To better highlight the advantages of constructing industry-neutral portfolios, Figure 5 plots the average returns and volatilities for both across and within industries L-S portfolios, and various ranking windows. The finding that average returns of the across-industries D-BEAM portfolios is very similar to the returns of within-industries portfolios suggests that D-BEAM is not an industry bet. The higher information ratio for within industries is driven by a lower volatility, rather than by higher average returns. The decrease in volatility ranges between 30% and 50% depending on the length of the ranking window. A similar improvement in the information ratio is observed for daily short-term reversal strategies, and also in this case the source of the improvement relies mostly on the decrease in the returns volatility.

[9] For example, for signals using returns up to market close on April 3, 2001, we skipped a day and buys the stocks at the market close on April 4 and sell the stock at close on April 5. For value-weighted portfolios, the weights are stock market capitalization at the close on April 3rd, 2001.

FIGURE 5

Average Returns and Volatility of Long-Short Daily EW Bond-Ranked Momentum across and within Industries



Note: The sample period is January 2001 to December 2017. This figure plots the average returns and volatilities, both annualized, of D-BEAM ranked across and within industries using various formation periods ranging from 1 to 20 days. The D-BEAM portfolios are equally weighted, and based on deciles. Portfolios are rebalanced daily and returns ignore transaction costs. Some of the values of this chart are reported in Figure 4.
Source: Barclays Research, Bloomberg, Compustat.

In sum, our results indicate that constructing industry-neutral portfolios, meaning buying winners and selling losers relative to their industry peers, lead to a better performance. This finding is of particular relevance to institutional investors and fund managers, and highlights the importance of "craftsmanship" in creating successful factor portfolios.[10]

To investigate the effect of the length of the ranking window in more detail, Figure 6 plots annualized information ratios for D-BEAM and short-term reversal L-S portfolios, ranked across and within industries. We find that D-BEAM information ratios are not sensitive to the length of the ranking window (i.e., from one to twenty days). This result is reassuring and guards against potential over-fitting by "optimizing" over a specific ranking window. We also find that for all ranking windows, D-BEAM information ratios are higher than that of short-term reversal returns.

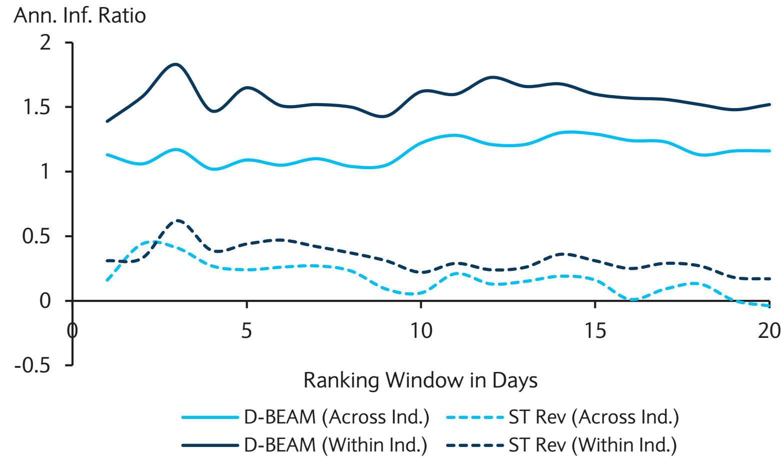
Information ratios for short-term reversals are almost always higher for industry-neutral portfolios than those portfolios ranked across all stocks regardless of industry. This finding confirms that industry effects are a key factor in constructing effective equity portfolios. The annualized average return for a short-term reversal strategy based on a ranking window of three days is, however, about 10%, and thus considerably smaller than what reported in previous studies. For instance, contrarian strategies that exploit the return reversals in individual stocks generate abnormal returns of about 1.7% per week (Lehmann, 1990) and 2.5% per month (Jegadeesh, 1990). This discrepancy is driven by two sources. First, our sample has a tilt towards large cap stocks, and once one moves past the small cap stocks, the profitability of short-term reversal strategies declines sharply with firm size.[11] Second, the profitability of going long losers and short winners has declined over time. Khandani and Lo (2007) document that the average daily return of a contrarian strategy is 1.38% in 1995, but by 2000, the average daily return drops to 0.44% and in 2007 it is only 0.13%.

[10] In a recent paper, Israel, Jiang and Ross (2017) discuss a number of small decisions in portfolio construction that taken together substantially enhance the long-term portfolio performance.

[11] Figure 3 displays the returns of value-weighted short-term reversal portfolios. In contrast, Lehmann (1990) and Jegadeesh (1990) findings are based on equally weighted portfolios.

FIGURE 6

D-BEAM and Short-Term Reversal Information Ratio across and within Industries



Note: The sample period is January 2001 to December 2017. This figure plots the information ratio for the D-BEAM and short-term reversal L-S portfolios ranked across and within industries and using various formation periods ranging from 1 to 20 days. The D-BEAM and Short-term reversal L-S portfolios are rebalanced daily and are based on deciles. Returns are equally weighted and ignore transaction costs. Some of the values of this chart are reported in Figure 4. Source: Barclays Research, Bloomberg, Compustat.

To highlight the additional informational content contained in each trading day included in the ranking window, we analyze the performance of portfolios ranked on past single day returns for D-BEAM or short-term reversal strategies. Figure 7 displays the average annualized return of strategies using signals based on past **single**-day return (bar chart) and based on past returns cumulated over **multiple** days (line charts). To understand the information content of the most recent day prior to portfolio formation, for multi-day signals, we also distinguish between signals including (dotted lines) and not including (solid lines) the most recent day-return immediately preceding the portfolio formation. The reason is that any signals containing the most recent day return may not be implementable as there may not be enough time between signal formation and transaction execution. The vertical dashed line indicates when 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 signals containing the return from the day immediately preceding the portfolio formation and may not be implementable.

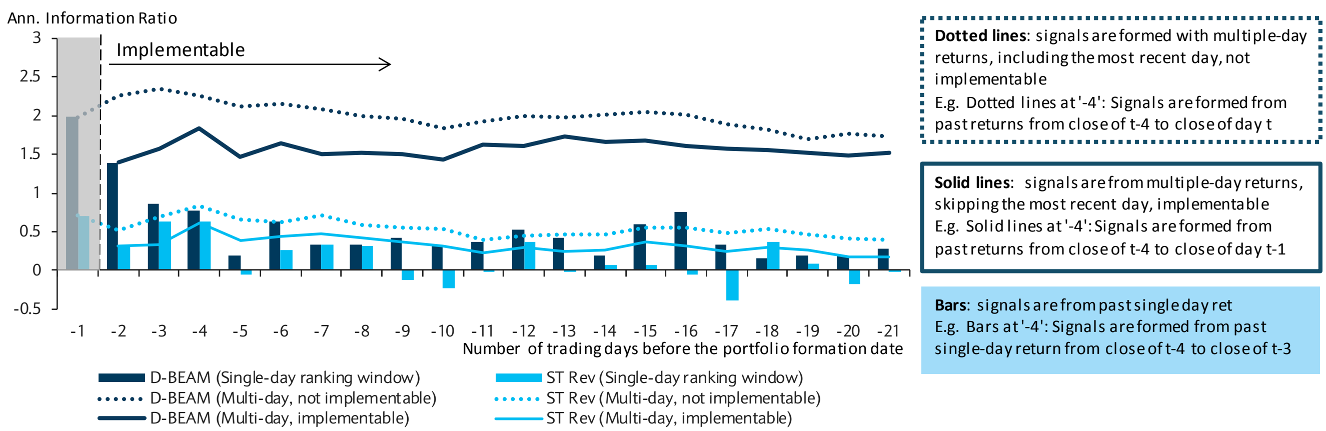
To clarify the notations, the signal associated to the dark blue bar at “-4” corresponds to the bond excess returns from the close of trading day t-4 to the close of trading day t-3, whereas the light blue bar corresponds to the short-term reversal strategy based on total equity returns from the same interval. 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 at “-4” represents the information ratio of the D-BEAM strategy based on the signal formation window from the close of trading day t-4 to the close of trading day t-1, and with the same one day holding period from the close on day t to the close on day t+1. The performance of this strategy can also be read in the second column in Figure 4, i.e., 18.2% (ranking window of three days).

Figure 7 highlights a few interesting observations on D-BEAM signals. First, it shows that a D-BEAM strategy that relies on a multiple-day ranking window generates higher information ratios than those based on a D-BEAM strategy that relies only on a single-day ranking window. In other words, the lines are always above the bars.

Another interesting observation from Figure 7 is that most of the valuable information is contained in the days immediately preceding the portfolio formation. First, the height of the bars declines the farther in the past the construction window is relative to the formation date. Second, the lines, which represent the average returns from multiple-day ranking windows, are positively sloped for the first four days, indicating that each additional day contains more information, and then they flatten out thereafter, showing that the D-BEAM strategy is insensitive to the length of the ranking window after the four-day point. Of note, the day immediately before the formation date contains a considerable amount of valuable information, producing an average return of 18% and an information ratio of 2, though as mentioned, we consider its inclusion non-implementable. Moreover, the dotted lines are always above the solid lines for each strategy, which indicates that including the most recent day return in the ranking window generates higher information ratio regardless of the length of the ranking window already used. For instance, the D-BEAM performance based on the four most recent ranking days (from t-4 to t) produces an annualized information ratio of 2.26 ('-4', dotted line) compared with an information ratio of 1.83 using a three-day ranking window from t-4 to t-1 ('-4', solid line). These findings are in line with the results discussed in Ben Dor and Xu (2015) 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. A lot of the signal information is contained in the trading days immediately preceding the portfolio formation.

FIGURE 7

Information Ratios of Strategies Based on Bond and Equity Signals by Ranking Window: Single- 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 L-S portfolios ranked within industries, and based on decile portfolios. The strategies have a 1-day holding period that buy stocks at close of day t and sell at close of day t+1. Returns ignore transaction costs. The bar chart displays the annualized information ratio of strategies based on ranking windows of one day, while the lines are based on returns 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. Some of the values of this chart are reported in Figure 4.
Source: Barclays Research, Bloomberg, Compustat.

In summary, our evidence indicates that the D-BEAM signal was robust to the length of the ranking window. Consistent with common market practice to hedge sector exposures, we find that ranking firms within industries results in similar average returns to ranking across industries but with lower volatility.

Additional analysis on the efficacy of D-BEAM signals

In this section, we present analysis in several dimensions to have a deeper understanding of the efficacy of D-BEAM signals. First, we examine D-BEAM performance across deciles and dissect D-BEAM L-S portfolio's better risk-adjusted performance over short-term reversal into two components: larger return differences and bigger volatility reduction through hedging. Next, to test whether D-BEAM signals have more predictive power of future returns than the equity short-term reversal signals, we perform a double sort using both signals. Finally, we examine to what extent the efficacy of the bond signals is affected by the liquidity of the underlying bonds, since bond liquidity might be a concern for signal efficacy, particularly on a daily level.

Monotonicity of returns across D-BEAM deciles

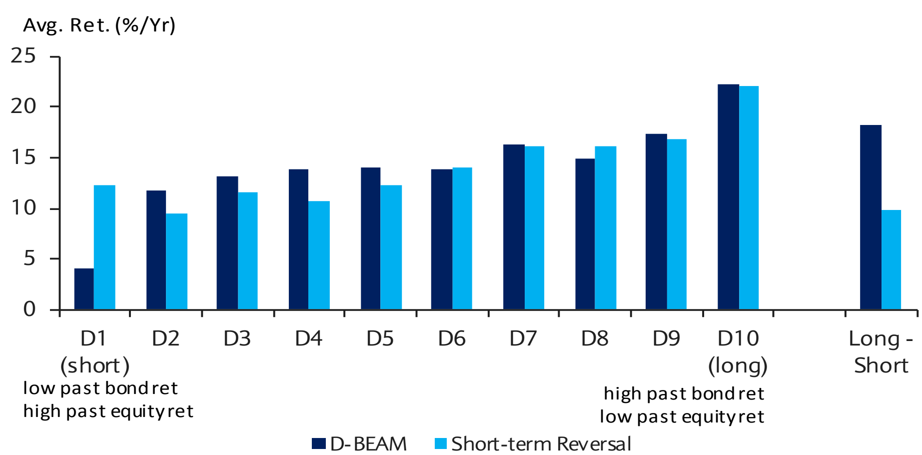
Many finance theories predict a monotonic relationship between expected returns and other variables (e.g., Patton and Timmermann, 2010). For instance, the CAPM predicts higher average returns for higher beta stocks, while theories of momentum predict higher average performance for higher past performance (Johnson, 2002). Figure 8 plots the average returns for all deciles, as well as the long-minus-short return differentials (winner-minus-loser for the D-BEAM strategy and loser-minus-winner for the short-term reversal strategy). The decile portfolios were aligned in the direction of predicted future returns by each signal. For D-BEAM signals, we start with the decile with the lowest past cumulative bond returns (D1, past bond losers), and each decile is increasing in past cumulative bond returns. On the other hand, with short-term reversal, we start with the decile with the highest past cumulative equity returns (past equity winners) as this is the group predicted to have the worst subsequent month return according to the short-term reversal strategy. As we move from left to right, each short-term reversal decile is decreasing in past cumulative equity returns.

Figure 8 shows that decile returns are mostly monotone with the strength of the D-BEAM signal. Specifically, a stronger signal is associated with higher average returns, though this relationship is not linear, and it flattens from the third to the eighth decile portfolios. For short-term reversal, the relationship is non-monotone, with average returns first move down from D1 to D2, but then increase from D2 to D3, flatten out from D3 to D9, and finally increase from D9 to D10. Also, D-BEAM and short-term reversal signals are similarly effective on the long leg as the two strategies have similar average returns for D10. However, D-BEAM signals are a lot more effective than short-term reversal signals in picking out the future losers, as the average returns of D-BEAM short-leg is only one-third of that of the short-term reversal short-leg. Thus, when we implement a long-short strategy, D-BEAM signals generated much higher average returns than the short-term reversal strategy.

For long-only investors, we note that the annualized return of the D10 bond-ranked portfolio is 22%, and is roughly 3 times the performance of the S&P 500 total return at 8% during the same period. This finding is relevant for long-only investors and shows that there are substantial benefits on using a credit signal overlay in a long-only portfolio.

FIGURE 8

D-BEAM and Short-Term Reversal Average Returns by Portfolio Decile



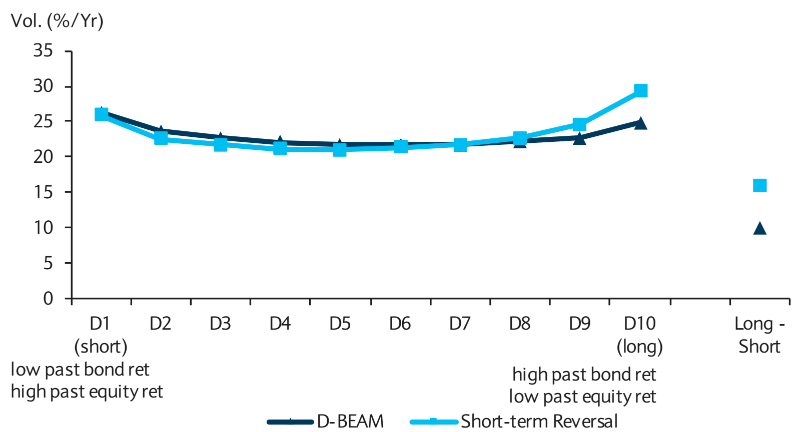
Note: The sample period is January 2001 to December 2017. This figure plots D-BEAM or short-term reversal annualized returns by decile. The annualized returns correspond to the (arithmetic) average daily returns multiplied by 251. Portfolios are rebalanced daily, ranked within industry, based on deciles and on a three-day ranking window. Returns are equally weighted and ignore transaction costs. Long-Short is defined as D10-D1. Source: Barclays Research, Bloomberg, Compustat.

Hedging efficacy of long and short sides

Figure 4 indicates that D-BEAM strategy returns had lower volatilities than short-term reversal strategies at various lengths of the ranking window. These results could be driven by two reasons: first, either D-BEAM long or short deciles have lower volatilities than those ranked on short-term reversal signals; or second, the D-BEAM top and the bottom deciles hedge each other more effectively than those ranked on the short-term reversal signals. To address this question, we look at the return volatilities of all deciles portfolios. Figure 9 plots the volatilities of all bond-ranked and equity-ranked decile portfolios, as well as the volatilities of the long-short portfolios. In line with the monthly evidence of Ben Dor and Xu (2015), we find that the volatilities of the bond-ranked decile portfolios are similar to those of the equity-ranked portfolios. However, the combination of top and bottom deciles in a long-short D-BEAM portfolio results in much lower volatility than short-term reversal. This finding suggests that top and bottom bond-ranked deciles hedge each other more effectively than short-term reversal deciles do.

FIGURE 9

D-BEAM and Short-Term Reversal Volatilities by Portfolio Decile



Note: The sample period is January 2001 to December 2017. This figure plots D-BEAM or short-term reversal annualized volatilities. The annualized volatilities correspond to the volatility of daily returns multiplied by $\sqrt{251}$. Portfolios are rebalanced daily, ranked within industry, based on deciles and on a three-day ranking window. Returns are equally weighted and ignore transaction costs. Long-Short is defined as D10 – D1.
Source: Barclays Research, Bloomberg, Compustat.

To shed further light on the hedging efficacy of D-BEAM deciles compared with that of short-term reversal over time, we look at the performance of bond- and equity-ranked portfolios in different sub-periods. Figure 10 displays the returns and volatility of decile portfolios for the entire sample (first four rows; the same data plotted in Figure 8 and Figure 9), and during the dot-com aftermath (2002-2003), the financial crisis (2008-2009) and all other years. The volatilities of the decile portfolios of D-BEAM are similar to those of short-term reversal in each sub-period. The long-short D-BEAM portfolio has, however, consistently lower volatility that that of short-term reversal. Furthermore, D-BEAM generates higher average returns than short-term reversal in every sub-period. More importantly, D-BEAM outperforms short-term reversal in bad economic times, with the largest outperformance during the financial crisis 2008-9, with an average return of 46% versus 10%.

FIGURE 10

Returns and Volatility of Decile Portfolios by Ranking Method and Period

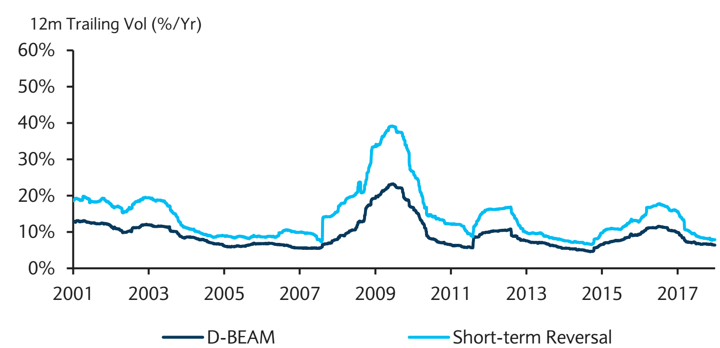
	Signal Source		Short Low Past Bond Ret High Past Equity Ret									Long High Past Bond Ret Low Past Equity Ret	Long-Short
			1	2	3	4	5	6	7	8	9	10	10-1
Full Sample 2001-2017	Bond	Avg. Ret. (%/yr.)	4.1	11.7	13.1	13.9	13.9	13.9	16.3	14.8	17.3	22.3	18.2
		Vol. (%/yr.)	26.3	23.7	22.7	22.1	21.7	21.7	21.7	22.1	22.7	24.8	9.9
	Equity	Avg. Ret. (%/yr.)	12.3	9.4	11.5	10.7	12.3	14.1	16.1	16.0	16.7	22.1	9.8
		Vol. (%/yr.)	25.8	22.6	21.7	21.1	20.9	21.3	21.7	22.6	24.6	29.2	15.8
Dot-com Aftermath 2002-2003	Bond	Avg. Ret. (%/yr.)	-6.2	5.4	3.0	12.1	6.9	5.5	15.5	16.3	17.5	22.3	28.5
		Vol. (%/yr.)	23.6	22.2	21.3	20.6	20.5	20.3	20.5	20.9	20.8	21.6	10.4
	Equity	Avg. Ret. (%/yr.)	4.6	7.8	11.9	7.9	7.9	10.8	12.1	0.1	11.5	25.4	20.8
		Vol. (%/yr.)	24.2	20.9	19.6	19.6	19.7	19.8	20.4	20.0	21.8	27.9	15.8
Financial Crisis 2008-2009	Bond	Avg. Ret. (%/yr.)	-8.5	6.7	9.5	7.7	7.7	3.9	16.0	13.8	24.5	37.5	46.1
		Vol. (%/yr.)	51.5	46.3	44.5	43.3	42.2	42.2	41.8	42.8	43.5	48.3	18.0
	Equity	Avg. Ret. (%/yr.)	19.5	6.4	9.1	1.4	4.8	11.7	14.2	11.9	12.2	30.0	10.5
		Vol. (%/yr.)	50.5	44.2	42.5	41.1	40.6	41.4	41.9	44.1	48.0	57.0	30.3
All Other Years	Bond	Avg. Ret. (%/yr.)	7.6	13.5	15.2	15.1	16.0	16.8	16.5	14.8	16.2	20.0	12.3
		Vol. (%/yr.)	20.2	18.1	17.3	16.8	16.7	16.6	16.7	17.1	17.7	19.3	7.9
	Equity	Avg. Ret. (%/yr.)	12.3	10.1	11.9	12.6	14.2	15.0	17.0	19.2	18.3	20.3	8.0
		Vol. (%/yr.)	19.8	17.3	16.7	16.2	16.1	16.4	16.8	17.6	19.0	22.2	12.2

Note: The sample period is January 2001 to December 2017. This figure plots D-BEAM or short-term reversal annualized returns and volatilities by ranking method (past bond returns or past equity returns) and sample period. The annualized returns correspond to the average daily returns multiplied by 251, and the annualized volatilities correspond to the volatility of daily returns multiplied by $\sqrt{251}$. Portfolios are rebalanced daily, ranked within industry, based on deciles and on a three-day ranking window. Returns are equally weighted and ignore transaction costs. D-BEAM and short-term reversal are defined as D10-D1.
Source: Barclays Research, Bloomberg, Compustat.

Since the benefits of long-short hedging may be time-varying, and the sub-period partitions in Figure 10 may not be fine enough to capture all important time dynamics, we also look at the volatilities over time on a month-to-month basis. Figure 11 plots the 12-month trailing volatilities of D-BEAM and short-term reversal returns. We find that D-BEAM trailing volatilities are lower than that of short-term reversal not only on average, but also in every market environment, and range between 46% and 85% of short-term reversal volatilities. In addition, the volatilities of D-BEAM returns are more stable over time, in stark contrast to the volatilities of short-term reversal that sky-rocketed during the financial crisis.

FIGURE 11

D- BEAM and Short-Term Reversal Trailing Return Volatility Over 12 Months



Note: The sample period is January 2001 to December 2017. This figure plots the trailing 12-month annualized volatility of the D-BEAM or short-term reversal portfolios. Portfolios are rebalanced daily, and based on a three-day ranking window. Returns are equally-weighted and ignore transaction costs. Source: Barclays Research, Bloomberg, Compustat.

Conditional double sort of bond and equity return signals

Figure 4 indicates that D-BEAM signals on average have more predictive power than short-term reversal signals at the two extreme deciles, as evidenced by their higher information ratios for the L-S portfolios. However, a few questions remain: do D-BEAM signals have additive predictive power to short-term reversal signals at different levels? Do short-term reversal signals provide additive predictive power to D-BEAM signals as well? Which one help the other more? To examine these questions, we perform a conditional double-sort using both signals. Figure 12 reports the results for using D-BEAM and short-term reversal signals formed from the most recent 3-day bond and equity returns respectively. To illustrate the double-sorting methodology, consider the “Bond Ret x Equity Ret” table (left panel in the Figure). We proceed in two steps. First, stocks are assigned to three buckets based on D-BEAM signals. Then, within each bucket stocks are further assigned to three past equity ret buckets. The column “Low-High” reports the return differential between low and high past equity return portfolios. To produce the “Equity Ret x Bond Ret” panel, we perform the same double-sorting described above, where we sort first on past equity returns and then on D-BEAM.

We find that conditioning on past equity returns (short-term reversal signals), sorting on the D-BEAM signals always generates a positive return spread and positive information ratio in all past equity return terciles. Specifically, the last column of Figure 12 shows that the return differentials range between 6% and 10%, and the annualized information ratios of D-BEAM high/low returns range between 0.93 and 1.21. In contrast, reversing the sorting order (i.e., sorting first on D-BEAM and then on past equity returns) does not lead to as much performance improvement in terms of information ratio as the sequential sort in the opposite order. One important source of D-BEAM terciles outperformance is that the combination of High-Low portfolios significantly reduces their volatility compared to the volatility of the High or Low portfolio in isolation. These results indicate that D-BEAM and short-term reversal signals both provide additive predictive power to each other, but D-BEAM helps short-term reversal more than the other way around.

FIGURE 12

Performance with conditional double sort on Past Bond Returns (D-BEAM Signals) and Past Equity Returns (Short-term Reversal Signals)

Conditional Double Sort (EW, Within Industries, Jan. 2001 - Dec. 2017)										
	Bond Ret x Equity Ret					Equity Ret x Bond Ret				
Ranking window = 3 days		Conditional Sort on Past Equity Returns					Conditional Sort on Past Bond Returns			
	First Sorting Dimension	Low	Medium	High	Low-High ST Rev	First Sorting Dimension	Low	Medium	High	High-Low BEAM
Avg. Ret (%/Yr)	Low Past Bond Returns	13.2	10.2	7.2	6.0	Low Past Equity Returns	12.4	19.2	22.8	10.4
Vol. (%/Yr)		26.9	22.2	23.4	11.3		26.6	24.0	24.5	8.6
Sharpe (Inf.) Ratio (Ann.)		0.39	0.36	0.19	0.53		0.37	0.70	0.84	1.21
Avg. Ret (%/Yr)	Medium Past Bond Returns	19.3	13.5	10.2	9.1	Medium Past Equity Returns	10.7	12.9	16.5	5.8
Vol. (%/Yr)		23.6	20.5	21.8	9.3		21.6	20.6	21.4	5.9
Sharpe (Inf.) Ratio (Ann.)		0.72	0.56	0.36	0.98		0.39	0.52	0.67	0.98
Avg. Ret (%/Yr)	High Past Bond Returns	22.4	16.8	15.0	7.4	High Past Equity Returns	7.4	10.7	14.3	6.9
Vol. (%/Yr)		24.4	21.6	23.6	10.1		23.4	22.2	23.5	7.4
Sharpe (Inf.) Ratio (Ann.)		0.83	0.67	0.53	0.74		0.21	0.37	0.51	0.93

Note: The sample period is January 2001 to December 2017. The D-BEAM and equity momentum portfolios are industry-neutral, rebalanced daily, based on terciles and a three-day ranking window. Returns are equally weighted and ignore transaction costs. Source: Compustat, Bloomberg, Barclays Research.

The effect of liquidity on D-BEAM performance

This section analyzes to what extent the efficacy of the D-BEAM signals is affected by the liquidity of the underlying bonds. Although liquidity represents a key determinant of asset prices, it is an elusive concept, and it is more easily recognized than defined. An additional complication in quantifying liquidity for corporate bonds is that they trade over-the-counter. Moreover, unlike equities or US Treasuries, actual corporate bond transaction data are not as widely available, and relatively few bonds trade on a daily basis. To measure bond-level liquidity we rely on Liquidity Cost Scores (LCS) developed by Konstantinovsky, Phelps and Ng (2016).

LCS measures the cost of an immediate, institutional-size, round-trip transaction, and is expressed as a percent of the corporate bond's price. Hence, LCS captures three dimensions of liquidity: tightness (i.e., the difference between buy and sell prices), depth (i.e., the size of the transaction) and immediacy (i.e., the speed to complete an order). More specifically, LCS relies on simultaneous, bond-level, bid-ask quotes issued by Barclays traders. However, the reliability of trader quotes may be uneven across bonds. The LCS methodology applies a number of adjustments to ensure that those quotes are executable, and not too narrow compared with the "true" market quotes. Another problem is that not all bonds comprising the IG and HY corporate indexes have a two-way quote on every trading day. For those non-quoted bonds, the LCS methodology populates bid and ask quotes by relying on an econometric model. LCS was launched in 2009 for all bonds that comprise the Bloomberg Barclays U.S. Corporate and High Yield indices (around 5,000 cusips at the time) with historical data available from January 2007, and over the years it has been extended to cover over 21,000 bonds around the world, and with a total outstanding of around $50 trillion in December 2017.

LCS is an absolute measure of liquidity. Hence, a LCS time series for a given bond does not show where the liquidity of that bond stands relative to its peers. To judge in a robust and quick way a bond's liquidity relative to similar bonds, Konstantinovsky, Phelps and Ng (2016) also developed another liquidity measure, the Trade Efficiency Score (TES). TES is a bond-level, intra-market, relative liquidity measure that combines transaction cost (i.e., LCS) and trading flows (i.e., volumes), and comes close to how traders think about market liquidity. To compute TES, each IG and HY bond is assigned to an OASD-adjusted LCS quintile (from 1 lowest to 5 highest), and to a monthly trading volume decile (from 1 highest to 10 lowest).[12] Then, the sum of LCS quintile and volume deciles are associated to TES buckets according to Figure 13. Low-TES buckets contain bonds with low LCS and high trading volume, and thus correspond to relative liquid bonds, whereas high-TES buckets correspond to more illiquid bonds.

FIGURE 13
Trade Efficiency Scores

Sum of LCS Quintiles and Trading Vol. Deciles	2 and 3	4 and 5	6	7	8	9	10	11	12	13-15
Trade Efficiency Score (TES) Deciles	**1 (Most Liquid)**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 (Most Illiquid)**

Note: The table reports the association between the sum of LCS quintile and volume deciles and TES buckets. Source: Barclays Research.

One possible explanation for the performance of D-BEAM is that bond prices quickly reflect relevant information for equity investors. In this section, we analyze whether the efficacy of the D-BEAM signal increases with the liquidity of the underlying bonds. To test this hypothesis, we apply a conditional double sort procedure. First, for each day we assign

[12] OASD stands for Option-Adjusted Spread Duration. The duration adjustment is necessary for relative-liquidity comparison of bonds with different duration.

stocks to 3 buckets (i.e., liquid, moderately liquid and illiquid) based on TES values of the underlying bonds. Then, we sort stocks in each TES bucket into three portfolios based on the corporate bond excess return signal. Finally, we calculate return of the D-BEAM portfolios as the return differential between high and low tercile portfolios. If corporate bond signals are more informative for more liquid bonds, we expect the performance of High minus Low (H-L) portfolios to have higher information ratios for lower TES values.

Figure 14 reports the performance (returns, volatilities and Sharpe/information ratios) for the three portfolios terciles in each TES bucket for the period from 2007 (i.e., when TES data are available) to 2017. The most interesting result is that H-L portfolio returns are always positive regardless of how liquid the corporate bonds are. Put differently, within each TES tercile, sorting on D-BEAM improves returns. Hence, we find that even in the least liquid segment of the corporate bond market, the D-BEAM signal remains effective.

Both returns and information ratios of D-BEAM portfolios are monotonic in the level of liquidity of the underlying bonds. For the most liquid bonds the annualized information ratio is around 1 and average returns are 9.5% per year, and the respective numbers are 0.58 and 4% per year for the least liquid bonds. However, the performances of D-BEAM based on the most liquid bonds falls short compared with that of D-BEAM based on the overall universe, which generates an annualized average return of 16% and an annualized information ratio of 1.6 for the same sample period February 2007-December 2017[13]. Including other bonds in the universe considerably improved the D-BEAM performance. A potential explanation of this finding is that not only the precision of the signal (i.e., liquidity of the underlying bonds) but also the intensity of the signal (i.e., magnitude of the bond excess returns) matters. In other words, by using a conditional double sort we sort bond returns conditional on a given TES bucket, rather than considering the largest bond returns in the overall universe. Alternatively, there might be benefits in combining D-BEAM signals with signal precision captured by TES.

FIGURE 14

Conditional Double Sort: TES x Bond Excess Returns

Conditional Double Sort (EW, within industries, Feb. 2007 - Dec. 2017)					
		TES x Bond excess returns			
Ranking window = 3 days		Conditional Sort on bond excess returns			
	First Sorting Dimension	Low	Medium	High	High-Low
Avg. Ret (%/Yr)	Low TES (liquid)	6.2	10.5	15.7	9.5
Vol. (%/Yr)		27.8	24.6	25.9	10.1
Sharpe (Inf.) Ratio (Ann.)		0.12	0.33	0.49	0.94
Avg. Ret (%/Yr)	Medium TES	11.4	10.9	16.0	4.6
Vol. (%/Yr)		26.1	23.9	25.4	7.5
Sharpe (Inf.) Ratio (Ann.)		0.33	0.37	0.54	0.62
Avg. Ret (%/Yr)	High TES (illiquid)	13.2	17.2	17.2	4.0
Vol. (%/Yr)		26.3	25.0	25.7	6.9
Sharpe (Inf.) Ratio (Ann.)		0.42	0.59	0.58	0.58

Note: The sample period is February 2007 to December 2017. The table reports the average portfolio returns, volatilities and Sharpe (Information) ratios using a 3 x 3 two-way sorts. The first dimension is TES and the second dimension is bond excess returns. The bond excess return sorting variable is based on the three-day ranking window. Portfolios are rebalanced daily. Returns are equally weighted and ignore transaction costs.
Source: Barclays Research, Bloomberg, Compustat.

[13] These performance statistics were generated by sorting individual stocks into 9 buckets each day based on the same D-BEAM signals (past 3-day cumulative bond excess returns) within each industry and calculating the L-S returns as the top bucket (highest past returns) over the bottom bucket (lowest past returns). The number of stocks in each bucket in this benchmark matches that in the double sort.

Diversification benefits of D-BEAM

Our previous analysis provides an overview of the univariate distribution of D-BEAM returns. This section investigates whether D-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 factor returns. Then, we look at a multivariate analysis, where we also control for the comovements between D-BEAM returns and other risk factors. Last, we look at whether including D-BEAM returns in various mean-variance efficient portfolios would improve their performance.

Correlations of D-BEAM with common equity risk factors

Figure 15 reports the time-series correlations between daily returns of a host of widely accepted and used risk factors constructed by Kenneth French, such as:

- The market excess return (**Mkt - Rf**): the return spread of the market return (value-weight return based on the CRSP universe) minus the risk-free rate (proxied by the one-month Treasury bill rate).
- The size factor (**SMB**): the return spread of small minus large stocks.
- The value factor (**HML**): the return spread of cheap (high book-to-market) minus expensive stocks (low book-to-market).
- The investment factor (**CMA**): the 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 one month between formation period and holding period.
- The short-term reversal factor (**ST REV**): the return spread of being long losers and short winners of the past 21 trading days.

The last two portfolios, industry-neutral Daily Short-Term Reversal and D-BEAM, differ from the other factors along three dimensions. First, the portfolios are industry-neutral: loser and winner stocks are selected 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. Third, these two factors were rebalanced daily while the other factors were rebalanced monthly.

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 and short-term reversal factors have also been extensively used for many years (Jegadeesh and Titman, 1993; Jegadeesh, 1990). On the other side, the CMA and RMW factors are proxies for the quality factors, respectively investment growth and profitability, that have been proposed more recently (Fama and French, 2015).

Figure 15 reports two types of correlation measures: the elements in the upper triangular matrix represent the Pearson product-moment correlation, whereas the elements in the lower triangular matrix represent the rank (Spearman) correlation. 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.

Since the correlation coefficients above the diagonal are similar to those below the diagonal, the two correlation measures lead to similar conclusion, thus suggesting that outliers are not driving our results. Of note, D-BEAM has a low correlation with all factors. Its largest correlations in absolute value are -0.37 and -0.33, respectively with the three-day and 21-day short-term reversal portfolios, and its rank correlations are even closer to zero. Put differently, we confirm for high-frequency data the result of Ben Dor and Xu (2015) that the information reflected in bond prices may not be the same as the information contained in stocks issued by the same company. The daily short-term reversal based on a three-day ranking window is also mostly uncorrelated with other portfolios. D-BEAM has a -0.14 Pearson correlation with the excess market return. Importantly, D-BEAM is uncorrelated with market returns, not only on average, but also across sub-periods. Not surprisingly, the largest correlation is with the short-term reversal based on a 21-day ranking window. The Value and Investment portfolios are positively correlated between each other, whereas the Profitability factor is negatively correlated with the market excess return.

FIGURE 15

Correlation Matrix

	Mkt - Rf	SMB	HML	CMA	RMW	MOM	ST Rev	Daily ST Rev	D-BEAM
Mkt - Rf		0.16	0.19	-0.20	-0.43	-0.40	0.30	0.19	-0.14
SMB	0.27		0.12	0.09	-0.25	0.00	0.01	0.02	0.03
HML	0.05	0.06		0.35	-0.14	-0.29	0.03	0.03	-0.07
CMA (Investment)	-0.08	0.07	0.39		0.11	0.24	-0.23	-0.09	0.09
RMW (Profitability)	-0.39	-0.27	-0.10	-0.07		0.38	-0.18	-0.13	0.10
MOM (Monthly)	-0.17	0.06	-0.09	0.08	0.25		-0.22	-0.07	0.08
Short-term Reversal	0.14	0.01	-0.03	-0.08	-0.09	-0.14		0.44	-0.33
Daily ST Rev (EW, Within Ind.)	0.10	0.05	0.00	-0.02	-0.09	-0.04	0.28		-0.37
D-BEAM (EW, Within Ind.)	-0.03	0.05	0.00	0.05	0.00	0.05	-0.18	-0.25	

Pearson Corr.

Rank Correlation

Note: The sample period is January 2001 to December 2017. The table reports the correlation matrix of daily returns between various risk factors, short-term reversal and D-BEAM strategies (last two columns). "Short-term Reversal" factor is based on 21-day ranking window. The Daily Short-term reversal and D-BEAM portfolios are ranked within industry, based on deciles and a three-day ranking window. Returns are equally weighted and ignore transaction costs. The level (Pearson) correlation is reported in the upper triangular matrix, the rank (Spearman) correlation is reported in the lower triangular matrix.
Source: Barclays Research, Bloomberg, Compustat, Kenneth French data library.

Risk-adjusted returns of D-BEAM

Next, we use a time-series (multivariate) regression framework to test whether D-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 D-BEAM or Short-Term Reversal 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. For each strategy, we look at the long-short returns based on deciles from by either ranking across the whole universe (first two columns) or within industries (last two columns). Significant abnormal alphas 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 alphas indicate that the investor has little to gain by getting exposure to the r_t strategy.

Figure 16 reports the Jensen's alpha for the raw returns (which correspond to those reported in Figure 4 for the case of k equals 3), the CAPM model (second row), the Fama-French 3 factor model (third row; FF3), the FF3 combined with momentum and short-term reversal based on a 21-day ranking window (fourth row; FF3+Mom+ST Rev), the Fama-

French 5 factor model (fifth row; FF5), and Fama-French 5 factor combined with momentum and 21-d short-term reversal (last row, FF5+Mom+ST Rev). We indicate with stars when the coefficients are significant at the 10% level or better. In contrast to the univariate correlation analysis reported in Figure 15, a multivariate regression simultaneously controls for multiple risk factors that might affect D-BEAM returns.

We find that D-BEAM (EW) returns have a large and significant risk-adjusted alpha, ranging between 18% and 21% per annum depending on the underlying risk model for industry-neutral portfolios and between 15% and 21% for portfolios across the overall universe. Hence, D-BEAM returns are unaffected by adjustment for common risk factors. The performance of short-term reversal is lower than D-BEAM, both unconditionally and after controlling for other risk factors. For instance, the EW short-term reversal alphas range between 2% and 10%, with a raw return of 10%.

FIGURE 16

Risk-Adjusted Alpha based on Various Risk Models

Alpha (%/Yr) based on	Across industries		Within industries	
	D-BEAM	ST Rev	D-BEAM	ST Rev
Raw returns	15.6***	9.2*	18.2***	9.8**
CAPM	16.4***	7.6	18.8***	8.5**
FF3	16.1***	7.7	18.6***	8.6**
FF3+Mom+ST Rev	20.9***	-1.7	21.5***	2.1
FF5	15.5***	9.4*	17.8***	9.8**
FF5+Mom+ST Rev	20.7***	-0.7	20.9***	2.9

Note: The sample period is January 2001 to December 2017. The table reports the intercept (annualized risk-adjusted alpha) of the regression of the D-BEAM and short-term reversal strategies on various risk factors. "CAPM" comprises of the market factor. "FF3" and "FF5" stand for the Fama and French three- and five-factor model, respectively. "Mom" stands for momentum (stock's cumulative return for t-12 to t-2 months), and value-weighted short-term reversal based on a 21-day ranking window and all CRSP U.S. stock universe. The D-BEAM and Short-term reversal portfolios are rebalanced daily and are based on deciles. Returns are equally weighted and ignore transaction costs. 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: Barclays Research, Bloomberg, Compustat, Kenneth French data library.

For completeness, Figure 17 reports the factor loadings for the case of EW industry-neutral D-BEAM returns. Note that by construction, the first row corresponds to the third column of Figure 16. The main finding is that D-BEAM returns have very low factor loadings, indicating that the D-BEAM factor is not spanned by other risk factors. The largest coefficient is -0.12 for short-term reversal, which implies that a ten percent return increase in short-term reversal is associated to 1.2% return decrease in D-BEAM. All in all, these findings suggest that D-BEAM not only produces a large and significant alpha, but also adds diversification benefits.

FIGURE 17

Factor Loadings of D-BEAM Returns

	Dep. Var. is D-BEAM (EW, Within Industries)				
Alpha (%/Yr)	18.8***	18.6***	21.5***	17.8***	20.9***
Mkt - Rf	-0.07***	-0.07***	-0.03	-0.05**	-0.02
SMB		0.07*	0.06*	0.07**	0.07**
HML		-0.05	-0.06*	-0.08	-0.08*
Mom			-0.02		-0.03
ST Rev			-0.12***		-0.12***
CMA				0.15**	0.07
RMW				0.08*	0.07
Adj. R^2	1.9%	2.4%	11.3%	3.3%	11.6%

Note: The sample period is January 2001 to December 2017. The table reports the regression results of D-BEAM returns on various risk factors. The D-BEAM portfolio is rebalanced daily, based on deciles and a three-day ranking window. Returns are equally weighted and ignore transaction costs. 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: Barclays Research, Bloomberg, Compustat, Kenneth French data library.

Effect of including D-BEAM strategies in mean-variance efficient portfolios

Another way to assess the potential value of D-BEAM to investors is to consider the incremental information ratio that could have been achieved using that strategy. The first eight columns of Figure 18 shows the average returns, volatilities and information ratios of the Fama and French five-factors (Mkt-Rf, SMB, HML, CMA, RMW), momentum (Mom), short-term reversal (ST Rev) and D-BEAM strategies for the sample period January 2001 - December 2017. All risk factors except D-BEAM are based on CRSP U.S. stock universe. The last six columns report the portfolio weights and performance of ex-post mean-variance efficient portfolios of various combinations of those strategies. Specifically, columns (9) considers including the Fama and French three factors (FF3), column (11) considers FF3 augmented by momentum and short-term reversal factors, column (13) considers the Fama and French five factors (FF5), and column (15) considers FF5 augmented by momentum and short-term reversal factors in the mean-variance portfolio. Columns (10), (12), (14) and (16) add D-BEAM to the opportunity set of investable assets considered in columns (9), (11), (13), and (15).

All seven factors generate positive returns, ranging from 1.7% for momentum to 11.9% for short-term reversal. The low average momentum return is driven by the momentum crash experienced in the first half of 2009 when most of the momentum gains dissipated. Combining factors generates higher information ratios, thus confirming the benefits of diversification. The performance improvement stems mostly from a reduction in volatility without any sacrifice in returns. Adding D-BEAM to the investable set of the FF3 factors more than triple the information ratio, from 0.60 to 1.99 for the FF3 portfolio and roughly double for the FF3+Mom+STRev, the FF5, and the FF5+Mom+STRev portfolios. D-BEAM substantially increases the portfolio returns in all cases and reduces the volatility in two out of four cases. The importance of including D-BEAM as an additional asset also manifests in the large weight, ranging from 39% to 75%, in the overall portfolio.

FIGURE 18

Ex-post Mean-Variance Efficient Portfolios

	Strategy Weight and Performance of Ex-Post Mean Variance Efficient Portfolio															
	Single Asset								Portfolio							
	Mkt_Rf	SMB	HML	Mom	ST Rev	CMA	RMW	D-BEAM	FF3		FF3+Mom+ST Rev		FF5		FF5+Mom+ST Rev	
										+D-BEAM		+D-BEAM		+D-BEAM		+D-BEAM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Mkt - Rf	1								0.32	0.12	0.04	0.02	0.16	0.12	0.07	0.03
SMB		1							0.68	0.09	0.29	0.06	0.22	0.10	0.19	0.08
HML			1						-0.01	0.04	0.09	0.07	-0.01	0.04	0.00	0.04
Mom				1							0.12	0.04			-0.02	0.00
ST Rev					1						0.46	0.27			0.21	0.21
CMA						1							0.09	-0.01	0.15	0.04
RMW							1						0.53	0.28	0.42	0.20
D-BEAM								1		0.75		0.54		0.48		0.39
Avg. Ret. (%/Yr)	8.0	4.5	2.2	1.7	11.9	2.1	4.5	18.2	5.6	15.2	7.5	13.7	4.8	11.4	6.0	11.4
Vol. (%/Yr)	19.0	9.0	9.9	15.6	13.7	6.0	7.1	9.9	9.3	7.6	6.9	5.4	3.97	5.23	3.88	4.19
Inf. Ratio (ann.)	0.42	0.50	0.22	0.11	0.87	0.34	0.64	1.83	0.60	1.99	1.08	2.54	1.22	2.18	1.54	2.71

Note: The sample period is January 2001 to December 2017. The table reports the portfolio weights in the ex-post mean-variance efficient portfolio for Fama and French three-factor (FF3) and five-factor (FF5) model (Mkt-Rf, SMB, HML, CMA, RMW), momentum (Mom) and short-term reversal (ST Rev) strategies. Those risk factors are all based on CRSP U.S. stock universe. The D-BEAM portfolio is industry-neutral, rebalanced daily, based on deciles (buying stocks in the top decile and selling stocks in the bottom decile) and a three-day ranking window. Returns are equally weighted and ignore transaction costs.
Source: Compustat, Bloomberg, Kenneth French data library, Barclays Research.

Consistency of D-BEAM performance

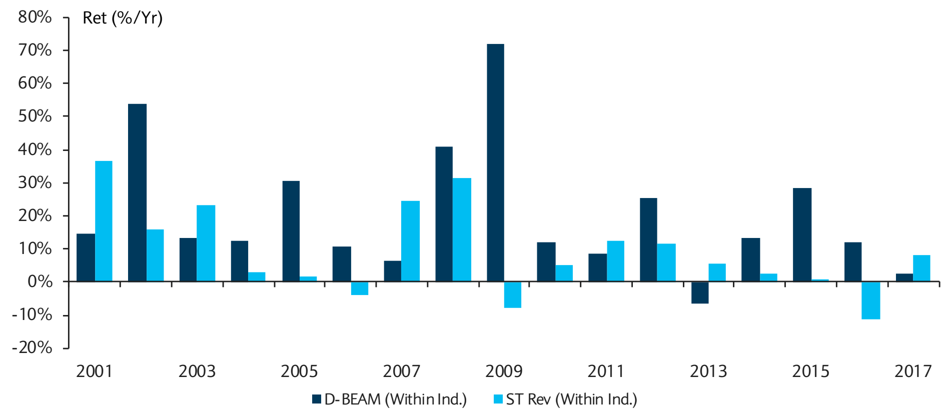
This section examines the consistency of D-BEAM performance both in-sample and out-of-sample. Within the sample period, we examine the stability of D-BEAM performance over time (years, day-of-the-week, and month-of-the-year) and in different economic states. However, many anomalies with significant in-sample results became insignificant after their initial publication (see, e.g., Linnainmaa and Roberts, 2018). For this reason, out-of-sample performance is often deemed to be the "gold standard" of the evaluation of a theory. This section provides two types of out-of-sample evidence on the efficacy of the D-BEAM signal: over time since the introduction of the D-BEAM strategy (2018) and across geographies. In the interest of space, all the results reported in this section are based on the D-BEAM strategy with a three-day ranking window and EW portfolio returns. We note, however, that the results are robust to different ranking windows.

Stability of the performance over time

To assess the profitability of the trading strategies in any specific sub-period, Figure 19 plots the average annualized return for D-BEAM and short-term reversal by year. Of note, D-BEAM returns have been positive in all years but one since 2001, including during the recent financial crisis and the dot-com bubble of the early 2000s. Moreover, D-BEAM returns were large during the 2008-2009 period. In contrast, short-term reversal strategy experienced a loss in 2009. Finally, D-BEAM returns have not declined over time.

FIGURE 19

D-BEAM and Short-Term Reversal Returns by Year



Note: The sample period is January 2001 to December 2017. This figure plots industry-neutral D-BEAM and short-term reversal portfolio returns. Portfolios are rebalanced daily, and based on a three-day ranking window. Returns are equally-weighted and ignore transaction costs. The annualized returns correspond to the (arithmetic) average daily returns multiplied by 251. Source: Barclays Research, Bloomberg, Compustat.

Many papers have documented strong seasonal patterns both in stock market index returns and in the cross-section of expected returns on common stocks.[14] We investigate the extent to which D-BEAM returns exhibit calendar effects: Panel A of Figure 20 looks at day-of-the-week effects and Panel B looks at monthly effects. Contrary to most stock anomalies, we cannot reject that D-BEAM returns are the same across different days of the week or different months (cf. last row in the tables). This finding holds for the long- and the short-leg, as well as for the D-BEAM (top minus bottom) portfolio.[15]

FIGURE 20

Panel A: Day-of-the-Week Effect

	D-BEAM (EW, Within industries)		
	Long	Short	Long-Short
Monday	-7.7	-28.4*	20.8***
Tuesday	26.7**	11.0	15.8***
Wednesday	28.1**	14.0	14.1***
Thursday	25.8*	9.8	16.0***
Friday	36.0***	11.7	24.3***
Adj. R^2	0.1%	0.0%	0.0%
H_0: Coefficients are equal (p-value)	0.22	0.27	0.62

Panel B: Monthly Effects

	D-BEAM (EW, Within industries)		
	Long	Short	Long-Short
January	21.7	-26.7	48.4***
February	14.5	1.5	13.0
March	49.2**	20.8	28.4***
April	58.6***	44.1**	14.5**
May	24.1	3.4	20.7**
June	-6.4	-16.8	10.4
July	7.8	-8.6	16.5*
August	7.7	6.9	0.8
September	-7.1	-26.7	19.6**
October	14.0	2.3	11.7
November	45.1*	22.8	22.3**
December	37.3**	24.3	13.0*
Adj. R^2	0.0%	0.0%	0.3%
H_0: Coefficients are equal (p-value)	0.21	0.28	0.14

Note: The sample period is January 2001 to December 2017. The dependent variable is industry-neutral D-BEAM (long, short, and long-short) portfolio returns. Portfolios are rebalanced daily, and based on a three-day ranking window. Returns are equally-weighted and ignore transaction costs. 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: Barclays Research, Bloomberg, Compustat.

[14] For instance, Keim (1983) finds that small stocks outperform large stocks in January, and Tinic and West (1984) show that high-beta stocks outperform low-beta stocks in January. More recently, Birru (2018) documents strong, predictable variation in the cross-section of returns across days of the week, with most anomalies exhibiting high returns on Mondays and low returns on Fridays, supporting the hypothesis that stock anomalies are sentiment-driven.

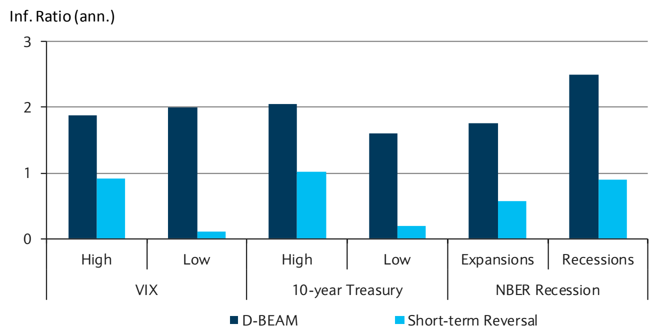
[15] We can also reject the presence of holiday effects for D-BEAM (results available upon request).

Stability of the performance in different economic states

So far, we looked at the performance of D-BEAM and short-term reversal strategies conditional on calendar time (i.e., years, day-of-the-week and monthly effects). We now analyze D-BEAM performance in different economic states. Figure 21 reports D-BEAM and short-term reversal information ratios depending on (i) the level of VIX (above or below the median, 17.2% in the sample 2001-2017), (ii) the level of the 10-year Treasury rate (above or below the median, 3.47% in 2001-2017), and (iii) NBER recessions vs. expansions. Of note, the chart below shows that the D-BEAM information ratio is higher than the short-term reversal information ratio in every type of market conditions (defined by the level of equity volatility, long-term interest rates or recessions vs. expansions). For instance, D-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 D-BEAM information ratio displays lower dispersion across states compared with that of short-term reversal.

FIGURE 21

D-BEAM and Short-Term Reversal Information Ratio in Different Economic States



Note: The sample period is January 2001 to December 2017. This table displays the information ratio for D-BEAM and short-term reversal in various states. Portfolios are rebalanced daily, are based on deciles and on a three-day ranking window. Returns are equally weighted and ignore transaction costs. The High (Low) level of VIX is above (below) its median (17.2% in the sample 2001-17). The High (Low) level of the 10-year Treasury rate is above (below) its median (3.47% in 2001-17). The recessions and expansions are classified by the NBER.
Source: Barclays Research, Bloomberg, Compustat, NBER.

Out-Of-Sample Performance: January 2018-July 2019

Finance research has uncovered many cross-sectional relations between predetermined variables and future stock returns. Most of these relationships, however, do not continue to hold with the passage of time (see, e.g., Linnainmaa and Roberts, 2018).

We introduced the D-BEAM strategy in Ben Dor, Guan and Rosa (*2018*) in April 2018. In the original study, the sample ended in December 2017, as is the case in this report. Since then, we have about one and a half years of new data that we can use to examine the out-of-sample performance of D-BEAM. Following Mclean and Pontiff (2016) method, we can split the sample January 2001-July 2019 in three non-overlapping periods: (i) the original study's sample period (2001-2017), (ii) the post-sample but pre-publication period (Jan. 2018 - Apr. 2018), and (iii) the post-publication period (May 2018 - July 2019). This decomposition exercise allows us to determine whether the D-BEAM performance is specific to the original sample period and the extent to which its performance has decayed since the publication of our first study.

Figure 22 provides a performance update in the out-of-sample period for D-BEAM and short-term reversal strategies, and for comparison the equal-weighted S&P 500 index. For convenience, the first three columns report the performance in the original sample (cf. Figure 4 for k = 3). The key finding is that D-BEAM has continued to deliver strong positive returns in the out-of-sample period. In particular, D-BEAM has generated average annualized returns of around 20% and 22% during January 2018–April 2018 and May

2018–July 2019, respectively, compared with 18% for the in-sample period. D-BEAM out-of-sample return volatility has been about 70% (pre-pub) and 80% (post-pub) of its in-sample volatility. The increase in returns coupled with the decrease in the volatility has boosted the D-BEAM information ratio to around 3 in the out-of-sample period. In contrast, the short-term reversal strategy has generated negative returns in the out-of-sample period.

FIGURE 22

D-BEAM Performance Update

	In-sample			Out-of-sample					
	2001 - 2017			January 2018 - April 2018			May 2018 - July 2019		
	S&P 500	D-BEAM	ST Rev	S&P 500	D-BEAM	ST Rev	S&P 500	D-BEAM	ST Rev
Avg Ret (%/Yr)	10.9	18.2	9.8	-0.3	19.5	-3.2	9.7	21.9	-9.3
Vol (%/Yr)	20.6	9.9	15.8	17.4	6.6	7.7	13.6	7.7	11.9
Inf Ratio (Ann)	0.53	1.83	0.62	-0.02	2.96	-0.42	0.72	2.83	-0.78

Note: The sample periods are January 2001 to December 2017 (left panel), January 2018 to April 2018 (middle panel), and May 2018 to July 2019. Average returns and volatilities are annualized by multiplying them respectively by 251 and $\sqrt{251}$. The information ratio is the ratio between average returns and volatility. D-BEAM and Short-term reversal portfolios are rebalanced daily, industry-neutral, based on deciles and on a three-day ranking window. Returns are equally-weighted and ignore transaction costs. The S&P 500 stands for the equal-weighted S&P 500 index (Bloomberg ticker: SPXEWTR Index). Source: Barclays Research, Bloomberg, Compustat.

International Evidence: European D-BEAM

The D-BEAM portfolio has generated an annualized return of 18% and an information ratio of 1.83 (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 is the D-BEAM signal 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 D-BEAM signal works internationally, the utility of the strategy will be broader. Ben Dor, Guan, Rosa and Zeng (2019) extend the BEAM study by looking at the relationship between corporate bond performance and subsequent equity returns in European markets.

Ben Dor et al. (2019) look at companies with listed equities on a European exchange starting in January 2012 and debt outstanding included in the Bloomberg Barclays Pan Euro IG or HY indices. Figure 23 reports the performance of D-BEAM and short-term reversals for various ranking windows.

Similar to the U.S., bond information is useful for equity momentum strategies at a daily frequency also in European markets. For instance, the long-short D-BEAM portfolio (constructed using a ranking window of 6 days) delivers an annualized information ratio of 1.30 for the period between 2012 and 2018, whereas the traditional short-term reversal portfolio (based on a ranking window of 3 days) generates an information ratio of 0.85 over the same period and with the same set of equities.

The most interesting aspect of Figure 23 is, however, that the BEAM signal has the same dynamics in European markets as it has in the U.S. Unlike equities, daily bond signals do not generate mean reversion in equity returns: past winners keep outperforming past losers. In addition, the day immediately preceding the portfolio formation date contains the most salient information. In terms of diversification benefits, the D-BEAM portfolio has highly significant alpha, and its returns do not exhibit significant loadings on the European Fama-French risk factors. Furthermore, the D-BEAM long-short portfolio has consistently lower volatility than that of short-term reversal. Also in Europe, the volatilities of the bond-ranked decile portfolios are similar to those of the equity-ranked portfolios, but the combination of top and bottom deciles in a long-short D-BEAM portfolio results in much lower volatility than short-term reversal.

FIGURE 23

Performance of D-BEAM and Short-Term Reversal in European Markets by Ranking Window

	Bond-ranked Momentum L-S Portfolios Buy Winners and Sell Losers					Short-term Reversal L-S Portfolios Buy Losers and Sell Winners				
Ranking Window (Past k days)	k=1	3	6	12	18	k=1	3	6	12	18
Avg. Ret. (%/Yr)	4.1	7.1	13.8	9.0	10.7	7.9	12.7	6.5	7.1	0.2
Vol. (%/Yr)	10.0	10.8	10.6	11.4	11.1	13.4	14.9	15.6	14.5	15.0
Inf. Ratio (Ann.)	0.40	0.65	1.30	0.79	0.96	0.59	0.85	0.42	0.49	0.01
Min. (%/Day)	-6.6	-6.8	-3.2	-7.1	-2.7	-4.2	-4.3	-4.9	-4.0	-5.5
Max. Drawdown (%)	-24.2	-25.3	-13.8	-16.7	-12.5	-20.7	-16.8	-22.3	-28.8	-28.7

Note: The sample is from January 2012 to December 2018. Returns and volatilities are annualized by multiplying them respectively by 251 and $\sqrt{251}$. Portfolios are rebalanced daily. Returns are equally weighted and ignore transaction costs. The information ratio is the ratio between returns and volatility.
Source: Bloomberg, Compustat, Barclays Research.

The long-short D-BEAM portfolio has positive and highly significant returns for the sample period 2001-2017, with a robust t-statistic of a 7.11, which far exceeds the Harvey, Liu and Zhu (2016) recommended threshold of 3.00. Nonetheless, as documented by Welch and Goyal (2007) and Harvey (2017), most of the factors identified as return predictors are dismissed in out-of-sample tests. We found strong empirical evidence of the D-BEAM concept in the out-of-sample period, with similar performance to that documented in the back-testing, and across geographies, providing strong support for its efficacy.

Conclusions

Standard economic theory suggests that in efficient markets stock prices adjust immediately to incorporate public information. Empirical studies have shown, however, that a few asset classes contain exploitable information for equity investors, even for liquid large-cap stocks. For instance, option markets may lead equity markets (see, e.g., Baltussen et al., 2012, and the references therein). In an important paper, Ben Dor and Xu (2015) show that corporate bond prices contain valuable information that is not fully reflected in equity prices. This paper extends their analysis by using high-frequency (daily), as opposed to lower-frequency (monthly), credit signals to construct equity portfolios.[16] We find that since 2001 a daily BEAM strategy has generated an annualized average return of 18%, with an annualized information ratio of 1.8. We document that D-BEAM portfolio performance improves in risk-adjusted terms when implemented in its industry-neutral hedging form. Furthermore, we show that D-BEAM returns have very low factor loadings, indicating that the D-BEAM factor is not spanned by other risk factors. Taken together, these findings suggest that D-BEAM not only produces a large and significant alpha, but also adds diversification benefits. Moreover, D-BEAM has shown consistent out-of-sample success not only over time (i.e., since the publication of our presentation in early 2018) and across geographies (i.e., in European markets). These results provide additional validation of our original U.S. D-BEAM findings. As corporate bonds are relatively illiquid compared with the equity market, there are concerns about whether illiquid bonds contain any useful information on future stock returns. We investigate to what extent the efficacy of the D-BEAM signals is affected by the liquidity of the underlying bonds. Using novel measures of corporate bonds' liquidity, we document that D-BEAM average performance is positive in all buckets sorted on the liquidity of the underlying corporate bonds. Finally, we note that most anomalies (i.e., patterns in average stock returns that are not explained by the CAPM) are concentrated in micro- and small-caps, which

[16] In a recent paper, Mao (2012) uses intraday data to show that corporate bond markets contribute more than 10% to high-frequency 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.

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 companies that issue corporate bonds are to a great extent large cap, it suggests that the D-BEAM strategy is implementable.

The results of this paper have important portfolio management implications. This work documents the performance of using high-frequency credit signals in systematic equity strategies, and serves as an "out-of-sample" test of the robustness of credit signals for equity investors. Building on the results of this paper, a key direction for future research would be to analyze the performance of a strategy that optimally combines different signals, such as combining daily BEAM and short-term reversal signals, or combining signal strength and signal precision (liquidity measures). Furthermore, credit signals may contain useful information for other equity strategies. For instance, bond returns around earnings announcements may have predictive power for post-announcement returns of the underlying stock. Finally, more work is warranted to better understand the economic sources and the reasons for the superior signal generated by bond pricing information. Moreover, a high-frequency strategy such as D-BEAM results in higher turnover, and investors need to consider transaction costs and taxes (i.e., Israel and Moskowitz, 2012; Frazzini et al., 2012). All are important topics left for future research.

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