Valuing biotechnology companies: Does classification by technology type help?

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Abstract

This paper explores whether conventional financial ratios can be used for portfolio construction in the biotechnology sector after the companies are classified into groups based on technology platforms such as DNA, biochemistry and bioprocessing technologies. We find some success in the use of financial measures after the classification is made indicating that they do a better job when comparing like firms. Appropriate risk adjustment is, however, critical to determining if superior performance is attained. This remains a challenge due to the difficulties in finding appropriate risk measures for the sector.
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INTRODUCTION

There are considerable challenges in the valuation of biotechnology companies due to the long lead times in the production of products and revenues from their intellectual capital assets. Two common techniques used in the valuation of companies in the finance literature are price earnings ratios and revenue multiples. There is, however, evidence of limited success in using these techniques in the valuation of biotechnology companies.[1–3]

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There are two main reasons why such methods may perform poorly in the valuation of biotechnology companies. First, the time horizon over which the financial measures are calculated may not correspond well to the product development horizon of a biotechnology firm. Second, the activities of the firms that make up the biotechnology sector may be too diverse preventing a comparison of like companies in the comparison of the financial measures.

The plan of this paper is to further analyse the valuation problem via consideration of the second reason and explore whether these financial measures perform better in portfolio construction when comparing 'like' firms when grouped by technology platform. This

paper outlines a strategy for grouping companies by technology platform and then applies that grouping strategy to the stocks that make up the *Nature Biotechnology* list of companies. Once the stocks are grouped by technology platform, an analysis of investment performance is reported.

CLASSIFICATION OF BIOTECHNOLOGY COMPANIES

The biotechnology sector covers a very broad range of companies with a diverse set of business models.[4] There are a variety of ways of classifying biotechnology companies in the literature including industrial grouping[5] and business platform.[6] The approaches to valuation include stage of development,[7] an area where real options type approaches have great potential,[8,9] and broad company type. This paper focuses on the role of company type. We adopt a classification of companies by technology platform along the lines of activity within the nuclei (DNA type technologies), activity with the cell but outside the cell nuclei (Biochemistry/Immunology type technologies) and activity at the intercellular level (Bioprocessing type technologies).[10] Our analysis makes use of this base classification structure, but also allows for firms to make use of a combination of these technologies. Thus, we consider the following seven classifications in our modelling structure: (1) DNA-based technologies; (2) Biochemistry/Immunochemistry-based technologies; (3) Bioprocessing-based technologies; (4) Medical instruments; (5) DNA/Biochemistry-based technologies; (6) Biochemistry/Bioprocessing-based technologies; and (7) Conglomerates. We acknowledge that is one of many possible ways of classifying the companies.

Thus, for each of the 440 companies that make up the *Nature Biotechnology* list of companies, we analysed data on the company's products and the technology platform(s) used in the production to classify the companies into one of these seven categories. For each company we are able to collect data on their revenue, R&D expenditures, profit and loss, beta (relative to the MCSI Global Index) and number of employees. Their beta is the standard risk measure in the capital asset pricing model. The calculation of this beta relative to a global index assumes an integration of world markets and its use for this set of stock spread across countries is comparable to the approach used in studies of risk at the national stock market level.[11–14]

In Table 1 we report the average values on each of these five measures across the seven classifications of companies. A visual comparison of these averages is also provided in Figures 1a and b. A comparison across classifications is made using the *F* test from the ANOVA procedure. The table also shows the calculated value of the *F* statistic and its associated *p*-value.

Average revenue was the lowest for DNA type companies as compared to the other six types of companies. As expected, revenue for conglomerates was substantially higher than

Table 1: Comparison of average company characteristics by classification type

	Number of companies	Revenue US$ (million)	Profit US$ (million)	R&D US$ (million)	Beta	Number of employees
DNA	40	17.165	−30.603	32.52051	1.484	223.725
Biochemistry	142	43.201	−16.253	26.30149	1.165	271.108
Bioprocessing	34	49.663	−23.653	24.35806	1.135	278.061
DNA and Biochemistry	30	246.057	−28.210	76.14483	1.346	951.607
Biochemistry and Bioprocessing	27	59.022	−5.544	18.784	1.077	324.238
Medical Instruments	18	28.906	−5.317	9.076471	1.062	285.632
Conglomerates	6	1604.633	303.233	403.8833	1.025	6230.667
F-test		17.783	21.140	38.921	3.393	21.326
		(0.000)	(0.000)	(0.000)	(0.003)	(0.000)

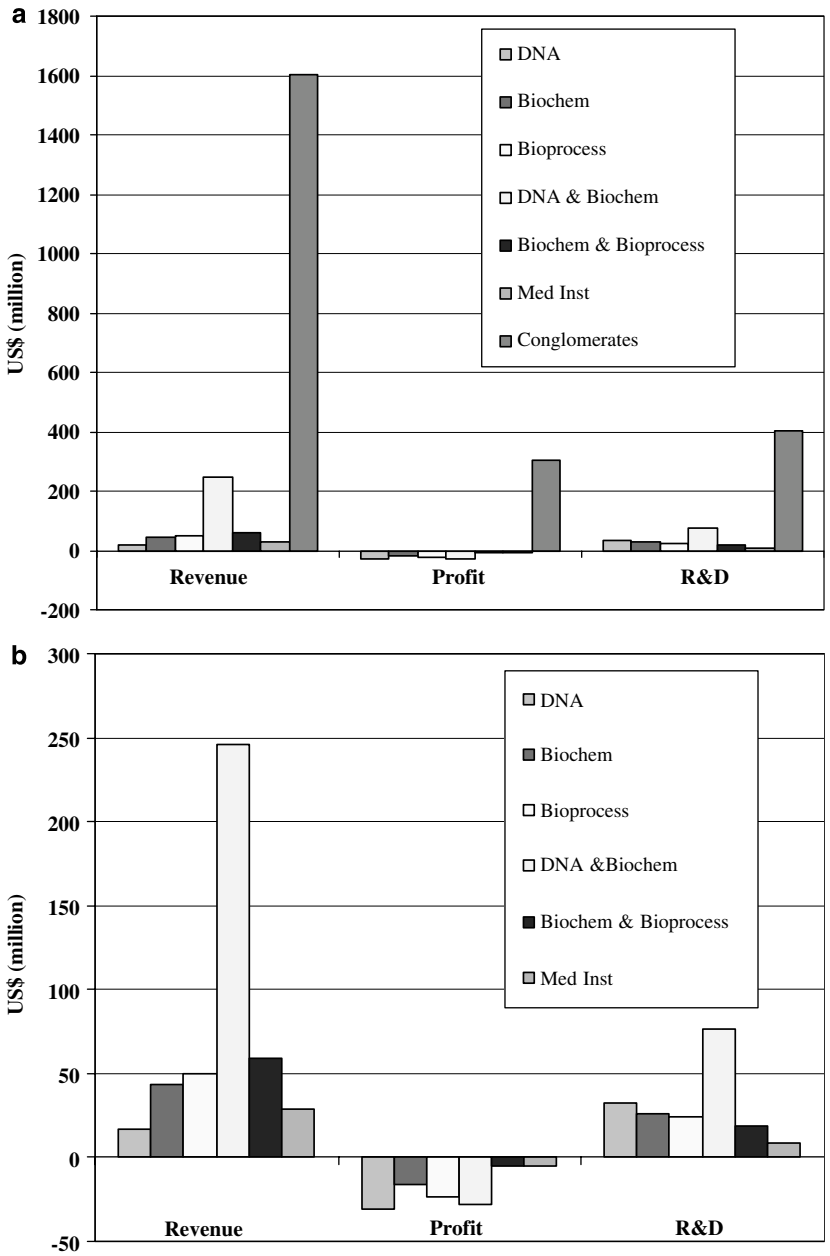

Figure 1: Revenue, profit and R&D (a) conglomerates included and (b) conglomerates excluded

the rest at an average of US$1.6bn. These differences were statistically significant ($p = 0.000$). All seven groups of biotechnology companies with the exception of conglomerates were not profitable. Average losses ranged from US$5.3m to US$30.6m. Differences in average P&L between the seven groups were statistically significant ($p = 0.000$). Similar differences were found in analysis of variables in R&D expenditure and these differences were statistically significant ($p = 0.000$). Average betas in the seven groups ranged from 1.025 to 1.484. DNA type companies recorded the highest betas (1.484), while conglomerates betas were the lowest (1.025). This observation can be explained

using an upstream/downstream model of product development in the biotechnology sector. Products of DNA type companies take longer to come to the market, the risk of these products being profitable are higher and therefore DNA companies can be expected to have higher betas than conglomerates who offer a wide range of products ranging from upstream to downstream. Differences in the beta between the seven groups were statistically significant ($p = 0.003$). Average numbers of employees ranged from 223 for DNA type companies to 6,230 for conglomerates. Differences in the average number of employees were statistically significant ($p = 0.000$).

PORTFOLIO PERFORMANCE BY CLASSIFICATION

For the three broadest classifications of company classification ((1) DNA-based technologies; (2) Biochemistry/ Immunochemistry-based technologies; (3) Bioprocessing-based technologies), we now explore the performance of portfolios based on firms in those classifications.

Several portfolios were then constructed from this universe of stocks in the *Nature Biotechnology* list. The first set of portfolios use revenue multiples as the selection criteria, while the second set of portfolios use price/ revenue ratios as the selection criteria. Price/ revenue ratios were used instead of price/earnings ratio as the vast majority of biotechnology companies that fell into the categories of DNA type technologies, Biochemistry type technologies and Bioprocessing type technologies had negative earnings over all of the three-year period. Price/earnings ratios used in this context would have been meaningless. The following portfolios are formed as a result of this construction exercise:

- PF 1: A portfolio of DNA technology companies.
- PF 1A: A portfolio formed from the top 30 per cent most attractive DNA type companies from a revenue multiple perspective.
- PF 1B: A portfolio formed from the top 10 per cent most attractive DNA type companies from a revenue multiple perspective.
- PF 1C: A portfolio formed from the bottom 30 per cent least attractive DNA type companies from a revenue multiple perspective.
- PF 1D: A portfolio formed from the bottom 10 per cent least attractive DNA type companies from a revenue multiple perspective.

- PF 2: A portfolio of Biochemistry technology companies.
- PF 2A: A portfolio formed from the top 30 per cent most attractive Biochemistry type companies from a revenue multiple perspective.
- PF 2B: A portfolio formed from the top 10 per cent most attractive Biochemistry type companies from a revenue multiple perspective.
- PF 2C: A portfolio formed from the bottom 30 per cent least attractive Biochemistry type companies from a revenue multiple perspective.
- PF 2D: A portfolio formed from the bottom 10 per cent least attractive Biochemistry type companies from a revenue multiple perspective.

- PF 3: A portfolio of Bioprocessing technology companies.
- PF 3A: A portfolio formed from the top 30 per cent most attractive Bioprocessing type companies from a revenue multiple perspective.
- PF 3B: A portfolio formed from the top 10 per cent most attractive Bioprocessing type companies from a revenue multiple perspective.
- PF 3C: A portfolio formed from the bottom 30 per cent least attractive Bioprocessing type companies from a revenue multiple perspective.

- PF 3D: A portfolio formed from the bottom 10 per cent least attractive Bioprocessing type companies from a revenue multiple perspective.

- PF 4A: A portfolio formed from the top 30 per cent most attractive DNA type companies from a price/revenue perspective.
- PF 4B: A portfolio formed from the top 10 per cent most attractive DNA type companies from a price/revenue perspective.
- PF 4C: A portfolio formed from the bottom 30 per cent least attractive DNA type companies from a price/revenue perspective.
- PF 4D: A portfolio formed from the bottom 10 per cent least attractive DNA type companies from a price/revenue perspective.

- PF 5A: A portfolio formed from the top 30 per cent most attractive Biochemistry type companies from a price/revenue perspective.
- PF 5B: A portfolio formed from the top 10 per cent most attractive Biochemistry type companies from a price/revenue perspective.
- PF 5C: A portfolio formed from the bottom 30 per cent least attractive Biochemistry type companies from a price/revenue perspective.
- PF 5D: A portfolio formed from the bottom 10 per cent least attractive Biochemistry type companies from a price/revenue perspective.

- PF 6A: A portfolio formed from the top 30 per cent most attractive Bioprocessing type companies from a price/revenue perspective.
- PF 6B: A portfolio formed from the top 10 per cent most attractive Bioprocessing type companies from a price/revenue perspective.
- PF 6C: A portfolio formed from the bottom 30 per cent least attractive Bioprocessing type companies from a price/revenue perspective.
- PF 6D: A portfolio formed from the bottom 10 per cent least attractive Bioprocessing type companies from a price/revenue perspective.

All the portfolios were price weighted, and their performance compared against a benchmark – the Amex Biotech Index on a one-, two- and three-year basis. Weekly price data between 2001 and 2004 from Bloomberg were used. The earnings data and revenue data were collected from Bloomberg and company websites.

Returns on each portfolio were measured against the benchmark portfolio to determine whether performance was superior over the one-, two- and three-year horizons. Following this, volatility-adjusted returns were measured for superior performance. In calculation of volatility-adjusted returns, volatility over the past period was used to adjust returns over the same corresponding period, that is, one-year volatility was used to adjust returns over one year.

Returns of both the test and benchmark portfolios were further adjusted for risk, as proxied by the Sharpe ratio.[15,16]

$$S = \frac{E(R - Rf)}{\sigma(R - Rf)} \tag{1}$$

where R is the portfolio return and Rf is the risk-free rate of return.

A comparison of the excess return of the two portfolios over the portfolio's required rate of rate as determined by the Capital Asset Pricing Model was determined using the Jensen's alpha.[17] The Jensen's alpha is calculated as

$$Jensen's\ Alpha = R - (Rf + (Market\ Return - Rf) \times Beta \tag{2}$$

Finally, the Treynor ratio[18] for both the test portfolio and benchmark was calculated and used as a means of comparison where the

market return was taken as the return on the MSCI Global Index. The Treynor ratio measures the excess returns of the portfolio over a riskless investment.

$$T = \frac{Rp - Rf}{Beta} \quad (3)$$

In calculating these portfolio performance measures, this study uses the standard ordinary least squares (OLS) beta and a Dimson beta[19] (with two leads and two lags) to adjust for any thin trading effects. Further all of the portfolio comparisons we make using these measures are pairwise, the more recent literature provides a variety of approaches to generalise these portfolio performance measures to compare across multiple portfolios.[20,21]

In Table 2, we report the raw returns for the benchmark portfolio and all of the portfolios formation on both a revenue multiple and price/revenue ratio basis across each of the classifications. These results reveal the following patterns. First, the initial classification by technology platform does not produce an improvement in portfolio performance relative to the benchmark. Within the classifications there is a general improvement in portfolio performance by selecting stocks rather than using all of the stocks in that technology platform classification. Within the DNA stock portfolios performance can be improved by selecting on a revenue multiple basis, although the result is less strong when selection is based on the price–revenue ratio. Within the

Table 2: Portfolio returns by company classification

	1 year	2 years	3 years
Benchmark	−0.00960	−0.00257	−0.00260
All companies by classification			
DNA companies	−0.02260	−0.00602	−0.00430
Biochemistry	−0.01495	−0.00335	−0.00358
Bioprocessing	−0.01679	−0.00279	−0.00300
Revenue multiple portfolios			
DNA top 30%	−0.02194	−0.00417	−0.00356
DNA top 10%	−0.03659	−0.00846	−0.00770
DNA bottom 30%	−0.01838	−0.00267	−0.00120
DNA bottom 10%	−0.00753	−0.00071	−0.00219
Biochemistry top 30%	−0.00588	−0.00121	−0.00123
Biochemistry top 10%	−0.00252	0.00052	0.00047
Biochemistry bottom 30%	−0.01794	−0.00312	−0.00290
Biochemistry bottom 10%	−0.01665	−0.00171	−0.00262
Bioprocessing top 30%	−0.01239	−0.00038	0.00035
Bioprocessing top 10%	−0.01436	−0.00079	0.00047
Bioprocessing bottom 30%	−0.02031	−0.00628	−0.00786
Bioprocessing bottom 10%	−0.00894	0.00025	−0.00240
Price–revenue ratio portfolios			
DNA top 30%	−0.02369	−0.00413	−0.00302
DNA top 10%	−0.00261	−0.00489	−0.02657
DNA bottom 30%	−0.02728	−0.00945	−0.00641
DNA bottom 10%	−0.02841	−0.01146	−0.00887
Biochemistry top 30%	−0.00996	−0.00033	−0.00069
Biochemistry top 10%	−0.00927	−0.00034	−0.00024
Biochemistry bottom 30%	−0.01892	−0.00405	−0.00325
Biochemistry bottom 10%	−0.01769	−0.00473	−0.00381
Bioprocessing top 30%	−0.01440	−0.00693	−0.00012
Bioprocessing top 10%	−0.00955	0.00079	0.00242
Bioprocessing bottom 30%	−0.02248	−0.00650	−0.00633
Bioprocessing bottom 10%	−0.02743	−0.00477	−0.00458

biochemistry stock, portfolios performance can be improved by selecting top stocks on either a revenue multiple or price–revenue ratio basis. Within the bioprocessing stock, portfolios performance can be improved by selecting top stocks on either a revenue multiple or price–revenue ratio basis. Relative to the performance against the benchmark there is a lack of improvement among the DNA stock portfolios. For the biochemistry and bioprocessing stock classifications there is, however, superior performance relative to the benchmark for the top stocks selected on either a revenue multiple or a price–revenue ratio basis. This shows the potential gain in classifying like firms before performing the portfolio selection.

The results on the raw returns show some promise on using the classification approach in the construction of portfolios. The different portfolios potentially have different risk characteristics and as such it is important to analyse whether the performance is superior on a risk adjusted basis. To explore this dimension of the analysis we use the Sharpe ratio, Jensen alpha and the Treynor ratio measures. In Table 3, we report a selection of the measures for the cases where they demonstrate superior performance on a risk-adjusted basis. We also show the *p*-value of the *t*-statistic comparing the performance measures for these cases, although we note that more formal comparison procedures have been developed.[22]

The performance of portfolios formed from the bottom 10 per cent least attractive DNA, the top 10 and 30 per cent most attractive biotechnology companies and the bottom 10 per cent least attractive bioprocessing companies on a revenue multiple basis, the top 10 per cent most attractive biochemistry companies, the top 10 per cent most attractive bioprocessing companies and the bottom 30 per cent least attractive bioprocessing companies on a price–revenue ratio basis were superior to the benchmark on a risk-adjusted basis using both the Sharpe and Treynor ratios, but not using Jensen's alpha. The performance of portfolios formed from the top 30 per cent most attractive companies on a price–revenue ratio basis were superior to the benchmark on a risk adjusted basis using only the Treynor ratio. In addition, the superior performance on the Treynor ratio was only found using OLS betas and was no longer the case once the Dimson correction for thin trading was made. Although the overall results are mixed, there is some evidence that selection of biotechnology companies following classifications by technology platform has some success in building portfolios that outperformed the benchmark Amex Biotechnology Index.

The results do show that appropriate risk adjustment is important in portfolio selection, and in particular the superior risk-adjusted performance no longer holds once a thin trading adjustment is made in risk estimation. All of the three portfolio performance measures that have been considered in this study proceed on the assumption that the CAPM holds true as the appropriate model of the risk-return trade-off. As such it is appropriate to consider a cross-sectional test of the CAPM on our dataset.

There is a vast literature on testing the CAPM and we use a two-pass approach,[23,24] although we do not adopt separate estimation and test periods because of lack of a sufficiently long sample. In addition, we also conduct the test at an individual stock level within the industry sector. The model to be estimated to test the CAPM is as follows:

$$\begin{aligned} Expectedreturn = {} & \gamma 0 + \gamma 1 Beta + \gamma 2 Revenue \\ & + \gamma 3 \frac{R\,\&\,D}{Revenue} + \gamma 4 P\,\&\,L \\ & + \gamma 5 Employees \end{aligned} \tag{4}$$

We estimate the model on all biotechnology companies, the three technology platform classifications of the companies that have been used in the portfolio formation analysis, plus another two classifications of the companies that use a mix of DNA and biochemistry technologies or a

Table 3: Summary measures of risk-adjusted portfolio performance

	1 year	2 years	3 years
Benchmark			
Sharpe ratio	−0.37909	−0.33551	−0.34445
Jensen alpha	−0.00594	0.00009	−0.00056
Treynor ratio	−0.01257	−0.00819	−0.00091
DNA companies: Bottom 10% revenue multiple basis			
Sharpe ratio *t* (*p*=0.001)	−0.07894	−0.01052	−0.02513
Jensen alpha *t* (*p*=0.322)	−0.00449	−0.00048	−0.00251
Treynor ratio *t* (*p*=0.017)	−0.01174	−0.00165	−0.00396
Biochemistry: Top 30% revenue multiple basis			
Sharpe ratio *t* (*p*=0.033)	−0.23146	−0.05937	−0.05989
Jensen alpha *t* (*p*=0.163)	−0.00442	−0.00127	−0.00161
Treynor ratio *t* (*p*=0.058)	−0.01743	−0.00450	−0.00474
Biochemistry: Top 10% revenue multiple basis			
Sharpe ratio *t* (*p*=0.001)	−0.06513	0.00560	0.00471
Jensen alpha *t* (*p*=0.428)	−0.00043	0.00058	0.00011
Treynor ratio *t* (*p*=0.004)	−0.00592	0.00027	0.00001
Bioprocessing: Bottom 10% revenue multiple basis			
Sharpe ratio *t* (*p*=0.020)	−0.17869	−0.00133	−0.04825
Jensen alpha *t* (*p*=0.328)	−0.00653	−0.00036	−0.00271
Treynor ratio *t* (*p*=0.067)	−0.01703	−0.00027	−0.00519
Biochemistry: Top 30% price revenue ratio basis			
Sharpe ratio *t* (*p*=0.081)	0.28421	−0.01819	−0.02968
Jensen alpha *t* (*p*=0.312)	−0.00655	−0.00003	−0.00100
Treynor ratio *t* (*p*=0.037)	−0.01383	−0.00091	−0.00156
Biochemistry: Top 10% price revenue ratio basis			
Sharpe ratio *t* (*p*=0.048)	−0.23459	−0.01664	−0.01520
Jensen alpha *t* (*p*=0.331)	−0.00614	−0.00008	−0.00056
Treynor ratio *t* (*p*=0.039)	−0.01397	−0.00105	−0.00102
Bioprocessing: Top 10% price revenue ratio basis			
Sharpe ratio *t* (*p*=0.030)	−0.17471	0.00967	0.04474
Jensen alpha *t* (*p*=0.941)	−0.00607	0.00111	0.00211
Treynor ratio *t* (*p*=0.043)	−0.01303	0.00529	0.00259
Bioprocessing: Bottom 30% price revenue ratio basis			
Sharpe ratio *t* (*p*=0.023)	−0.05397	−0.12974	−0.12971
Jensen alpha *t* (*p*=0.619)	0.00214	−0.00601	−0.00659
Treynor ratio *t* (*p*=0.017)	−0.00269	−0.00724	−0.00711

mix of biochemistry and bioprocessing technologies. The results of estimating the model are reported in Table 4 and show OLS estimates of the parameters and *p*-values on the significance of the variables in parentheses. To the extent that the CAPM is the appropriate model of the risk-return relationship then only the beta variable should be significant.

The CAPM is not a good model for explaining cross-sectional returns in the portfolio of all biotechnology companies, and for each of the cases where the firms can be classified as using a single technology platform. In these specifications the beta and the extra market factors are generally insignificant (the exception is the P&L variable in the case of DNA stocks). For those companies whose underlying technologies are a combination of DNA and biochemistry technologies, the beta coefficient was positive and statistically significant and the extra

Table 4: CAPM tests on biotechnology stocks

	All stocks	DNA stocks	Biochemistry stocks	Bioprocessing stocks	Combined DNA/ Biochemistry	Combined bioprocessing biochemistry
Beta	0.000126	0.002072	−0.001570	−0.000412	0.013024	−0.008552
	(0.915)	(0.378)	(0.236)	(0.881)	(0.007)	(0.049)
Revenue	−0.000001	−0.000180	−0.000006	0.000009	0.000008	−0.000032
	(0.874)	(0.084)	(0.537)	(0.404)	(0.737)	(0.129)
R&D/revenue	−0.000010	−0.000170	0.000002	0.000030	−0.000004	−0.001250
	(0.365)	(0.593)	(0.923)	(0.551)	(0.172)	(0.012)
P&L	0.000001	0.000161	0.000029	0.000021	0.000016	0.00003
	(0.961)	(0.011)	(0.238)	(0.465)	(0.751)	(0.615)
Employees	0.000001	0.000014	0.000003	0.000002	−0.000002	0.000007
	(0.440)	(0.103)	(0.162)	(0.877)	(0.786)	(0.195)

market factors all statistically insignificant. Thus, there is greater support for the CAPM in these more diversified companies that use a combination of DNA and biochemistry technologies. A contrasting pattern was seen in companies whose underlying technologies were a combination of biochemistry and bioprocessing technologies. The beta is found to be significantly negative, along with the extra market factor of R&D/revenue.

Overall, the results of testing the CAPM are not strongly supportive. This suggests care in the use of the portfolio performance measures that all are CAPM based. It may be possible to overcome some of these limitations by testing based on portfolios as suggested in the Fama-MacBeth approach, or by adopting a variant of the more general three factor Fama-French model.[25–27] The behaviour of high-technology stocks are, however, known to be problematic for asset pricing tests.[28]

CONCLUSION

This paper has explored whether conventional financial ratios can be successfully used for portfolio construction in the biotechnology sector after the companies are classified into groups based on technology platforms. We find greater promise in the use of financial measures after the classification is made indicating that they do a better job when comparing like firms. There is, however, less evidence of superior portfolio performance on a risk-adjusted basis. In part, this appears to be due to the difficulties of finding appropriate risk measures for the sector.

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