R&D MANAGEMENT

Robust future-oriented technology portfolios: Black–Litterman approach

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We propose a new way of constructing more robust technology portfolios to overcome the weaknesses of previous technology portfolios based either on the judgments of experts or on quantitative data such as patents. Instead of using historical data, the method of nonlinear forecasting enables us to forecast the future number of patent citations and accordingly, to use the forecast as a quantitative proxy for future returns and risks of technologies. Using the Black–Litterman portfolio model, we improve the accuracy of inputs by combining the future views of experts with the future returns and risks of technologies. As a consequence of this, the portfolio becomes strongly future-oriented. With our approach, corporate managers use both experts and data more effectively to build robust technology portfolios. In particular, our method is of great help for companies launching new businesses because the method avoids heavy dependency on internal experts with little knowledge about emerging technologies. A company entering the molecular amplification instrument market is exemplified herein.

1. Introduction

By any measure, the concerns of launching and growing new businesses are beyond any other concerns in companies today. However, the perception persists that a new business is an expensive, easy-to-fail gamble (Campbell and Park, 2005). Over the last several decades, 44% of new businesses by global top-tier firms have led to failures (Garvin, 2004). To date, the rate of failures has not been significantly reduced. This is why so many companies hesitate to drive new businesses. New business development has proved to be risky and is expected to become riskier now than ever before.

To overcome this fear of failure, managers are angling for emerging technology-driven new businesses with innovation opportunities. At the heart of these opportunities is a technology portfolio (Sadowski and Roth, 1999; Kfir, 2000). Technology portfolio is the result of a dynamic decision process on how technologies should be directed and organized (Jolly, 2003). Conceptually, there are three types of technology portfolio. A relatively static

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technology portfolio emphasizes the separate financial evaluation of each technology over the medium to long term (Floricel and Miller, 2003). Contrastingly, a dynamic contingent technology portfolio in high-velocity sectors is reorganized frequently and rapidly based on the latest concrete information, focusing on the short-term adaptation (Floricel and Ibanescu, 2008). The third portfolio is used to make a shift to new innovation over the short to medium term (Jolly, 2003; Floricel and Ibanescu, 2008). Among these, we focus on the third because it is appropriate to address earlier-mentioned issues of new businesses.

For successful new businesses, key technologies should be nurtured internally to sustain competitive advantages, but key technologies are hard to identify (Van Wyk, 2010). Furthermore, it is even harder to optimize a technology portfolio over a future time horizon with appropriate regard to future returns and risks (Dickinson et al., 2001). Nevertheless, if such technology portfolios can be constructed, then the challenge of achieving a consensus on new businesses becomes much easier.

In practice, managers typically depend on internal experts to build a technology portfolio (Cooper et al., 2001). Internal experts are good at assessing the value and potential of corporate technologies but in most cases have little knowledge on the core technologies of new businesses. When others question the portfolio, the experts have difficulty in rationally defending their judgments (Van Wyk, 2010). Although there are a number of ways to construct qualitative portfolios to improve the judgments of experts, these methods have been of limited use, and significant practical improvements have rarely occurred.

As a remedy, some companies use external experts such as consultants to build technology portfolios and identify opportunities. Consultants have professional knowledge and experience about the value, potential, and synergy of the core technologies of new businesses. Note that a technology portfolio for any potential new business is usually confidential. Most companies are thus reluctant to ask external experts to design technology portfolios based on proprietary information for new endeavors. Additionally, external experts frequently misjudge corporate technological and organizational capabilities. Consequently, the consultants produce promising but inappropriate portfolios for the particular companies with which they are temporarily working.

Instead of relying on external experts, another way to obtain knowledge is to use quantitative data, such as journal articles and patents. Among various types of quantitative data, recent technology portfolio studies have focused on patents. Ample patent data allows researchers to perform a variety of analyses, including evaluation and exploitation of corporate technologies and technological capabilities, identification of technology-based business opportunities, and technological positioning (Ernst, 1998; Fabry et al., 2006; Chang, 2012). Many managers have doubts about the accuracy of purely patent-based technology portfolios, however, because assessment of portfolios is often very different from the differing perspectives of experts (Pachomovsky and Wagner, 2005). Moreover, patents have been criticized for being conceptually outdated, showing not the future but the past of technologies (Khan and Dernis, 2006; Lee et al., 2012).

These shortcomings suggest the necessity of combining the views of experts with quantitative data, particularly when companies construct technology portfolios for new businesses. As a solution, we propose the joint use of patent citation forecasting and the Black–Litterman approach to developing portfolios. The research finds that the proposed solution could improve technology portfolios that are lopsided according to either the judgments of experts or the quantitative data. Reviewing previous approaches to technology portfolios, we explain our methodology. Subsequently, this paper provides an illustrative empirical analysis of a company engaged in launching a new business. The paper ends with a discussion and conclusions.

2. Review of existing approaches to technology portfolios

From the outset, simple portfolio matrices such as the Boston Consulting Group matrix and other variations have been widely used (Slatter, 1980; Capon and Glazer, 1987; Roussel et al., 1991). Because financial uncertainty and the cost of failure have soared to unprecedented levels, however, managers have raised serious concerns about the effectiveness of simple qualitative methods based on expert judgments (Cooper et al., 2000). Analyzing the limited success of simple technology portfolios, a study by Tritle et al. (2000) found that these approaches by experts fail to address qualitative judgments in the right way.

Recognizing these problems, some researchers have tried to improve qualitative methods of portfolio analysis based on the notion that managers have made little use of mathematical models to construct technology portfolios due mainly to complexity (Cooper et al., 1997). Formerly simple portfolio matrices have been developed into new portfolio maps and bubble diagrams (Matheson et al., 1994;

Cooper et al., 2001). Some research has focused on improving the quality of the judgments of experts and suggesting new scoring methods (Hall and Naudia, 1990; Coldrick et al., 2005), as well as on decision analysis-based methods such as analytical hierarchy process, multi-attribute utility theory, decision trees, and fuzzy theory (Jackson, 1983; Suh et al., 1994; Hsu et al., 2003; Duarte and Reis, 2006). Other studies have focused on the alignment of technologies with business strategies. The strategic bucket approach is a typical example of those alignment methods (Cooper et al., 2001).

Among existing quantitative methods, simple financial methods using various profitability, and return indicators such as net present value have been dominant in practice (Martino, 1995; Cooper et al., 2001). However, these measures are not able to take into consideration the differences in future risks. To tackle this issue of forecasting, some studies have modified existing measures with real option theory (Mitchell and Hamilton, 1988; Perlitz et al., 1999; Barnett, 2005). The resulting complexity of mathematical models such as multi-objective programming (Stummer and Heidenberger, 2003; Carazo et al., 2010) is a barrier to widespread adoption by managers looking to start new businesses with these methods (Graves et al., 2000). Furthermore, financial methods, as well as some qualitative methods such as scoring, assume that technologies are mutually independent. Many studies have criticized this assumption, stressing the impracticality of independence among emerging technologies (Martino, 1995; Dickinson et al., 2001).

As modern finance portfolio theories have developed, some researchers have adopted frameworks that emphasize the diversification of unrelated technologies in order to reduce risk (Graves et al., 2000; Ringuest and Graves, 2005). These theories agree with the notion that portfolios are improved by increasing technological diversity (Granstrand et al., 1997). In contrast, strategy-focused scholars disagree with this view, concentrating instead on strategically important factors. According to strategy-focused scholars, technological synergy has huge potential for future returns and is thus more important than risk reduction (Dickinson et al., 2001; Lin and Chen, 2005). To identify such factors, the judgment of experts is inevitable.

The final approach to note is the patent portfolio. Originally, patent portfolios were used to understand the status of corporate intellectual properties such as technology valuation and technological capability assessment. Patent portfolios have subsequently been extended to identify and exploit technological and business opportunities (Ernst, 1998; Fabry et al., 2006; Chang, 2012). Regardless, patent-based approaches are not free from the weaknesses noted earlier.

It is currently evident that there is no single best method for the development of technology portfolios. Leading companies thus adopt a combination or hybrid approach, using more than two portfolio methods per business (Cooper et al., 2001). In this regard, there have been many attempts to combine qualitative judgments with quantitative methods, aiming at both practical usefulness and theoretical rigor. Examples include methods of integrated framework (Linton et al., 2002) and fuzzy theory with real options (Wang and Hwang, 2007). Our study is in line with these efforts, suggesting a new hybrid method for technology portfolios.

3. Methodology

This section examines the overall process of the proposed method. As involvement of many techniques and complex models may lead to conceptual misunderstanding and imprecise use in practice, the suggested method is designed to be executed in two steps in terms of inputs and outputs. The first step uses patent data, calculating the expected number of future citations and their variances as proxy measures for future returns and risks of technologies. The second step integrates the differing perspectives of experts into the future returns and risks of technologies through a Black–Litterman model. As a consequence of this, the portfolio constructed becomes future oriented and provides corporate managers with balanced views on technologies.

3.1. Patent citation forecasting: least absolute deviation estimation

Current approaches to technology portfolios attempt to deal with uncertainties, but the approaches tend to stay at suggesting methods with simulation results, without going beyond existing limitations. This is mainly due to data unavailability. Return and risk data can be easily collected in finance, but not in other industries. Overcoming this limitation, we forecast future patent citation by using the technique of curve fitting and the Bass model. Accordingly, we calculate the expected number of citations and variances, and use the calculations as proxy measures of future returns and risks of technologies.

The scatter-plot of patent citations of molecular amplification technologies show typical nonlinear growth patterns. The growth of more user-relevant technologies such as amplification, however, is influenced by user characteristics. Innovators adopt new technologies at early stages because innovators perceive the advantages, but others usually wait on adoption until they feel some pressure. In contrast, users rarely influence the adoption of basic technologies, such as automation. Considering these user behaviors, we match technologies with appropriate forecasting methods, including exponential curves, S-shaped curves, and the Bass model. These methods are proven to be appropriate for describing typical technological growth processes (Porter et al., 1991; Daim et al., 2006).

The estimation method also plays an important role in forecasting unknown values based on the technique of curve fitting. There are three widely used estimation methods, which include nonlinear programming, least squares regression, and least absolute deviation (LAD) (Lawrence et al., 2009). Among these, LAD is found to be more robust than the others because it is resistant to outliers (Lawrence et al., 2009). Specifically, LAD outperforms least squares regression in terms of accuracy and statistical inferences when errors are large and heterogeneous. Patent citation forecasting is such a problem in that future citation counts are severely affected by many factors and very different across individual patents, and thus LAD fits are safer and should be the fitting technique of first choice. The formulation of LAD is as follows (Vanderbei, 2007).

$$min\sum_{t=1}^{N}\left|FR_t - S_t\right|$$

where FR_t denotes a function with unknown parameters, and S_t denotes the real value of data. Thus, the formula seeks the estimated values of unknown parameters that minimize the sum of the absolute values of residuals. Another advantage of LAD is that it always does conservative forecasting with relatively underestimated values. When a company is risk averse regarding new technologies or businesses, LAD is the best estimation method.

3.2. Black–Litterman portfolio model

The Black–Litterman model enables experts to combine their views regarding the future performance of various technologies with forecasts of expected returns and risks (Black and Litterman, 1992). Furthermore, it takes advantage of translating relative views into quantitative inputs for the portfolio. Experts rarely speculate on the absolute returns of technologies. In most cases, they instead provide comparative rankings of technologies that are predicted to outperform or underperform relative to other technologies. Using relative judgments, current models reduce biases due to absolute judgments. Note that conservative approaches, including LAD, are consistently used to reflect prevalent risk-averse attitudes.

Black–Litterman portfolio construction is comprises three steps. The first step is calculating the excess equilibrium returns of technologies, second is expressing the views of experts, and third is combining the views of experts with the excess equilibrium returns. To calculate the excess returns, the starting point is the capital asset pricing model (CAPM) as follows.

$$E(r_i) - r_f = \beta_i\left(E(r_m) - r_f\right)$$

where $E(r_i)$, $E(r_m)$, and r_f are the expected return on technology i, the expected return on the market portfolio, and the risk-free rate of return, respectively. The expected excess return on technology i is defined as the difference between the expected return on and the risk-free rate of return, denoted by $E(r_i) - r_f$. In other words, this is a technological risk premium, meaning the amount of returns by taking the risk of technology i. A technology portfolio is optimized to maximize the excess equilibrium returns of technologies with the lowest tolerable level of risk. A market portfolio is composed of all assets, but in our model consists of all candidate technologies for a company's new business. We divide the number of patent citations of a technology by the total number of patent citations of all candidate technologies and use this as the proportion of a technology in the market portfolio. The number of patent citations is used as a proxy measure of technological value.

In the CAPM, β_i is $\mathrm{cov}(r_i, r_m)/\sigma_m^2$ where σ_m^2 denotes the variance of the market portfolio. Then, let us denote by $\omega_b = (\omega_{b1}, \ldots, \omega_{bN})'$, which is the market capitalization weight for all candidate technologies. The return on the market portfolio can be written as $r_m = \sum_{j=1}^{N}\omega_{bj}r_{mj}$. Then, by the CAPM, the expected excess return on technology i becomes as shown below.

$$\begin{aligned}\Pi_i &= \beta_i\left(E(r_m) - r_f\right)\\ &= \frac{\mathrm{cov}(r_i, r_m)}{\sigma_m^2}\left(E(r_m) - r_f\right)\\ &= \frac{E(r_m) - r_f}{\sigma_m^2}\sum_{j=1}^{N}\mathrm{cov}(r_i, r_j)\,\omega_{bj}\end{aligned}$$

We can express this in the matrix-vector form as follows.

$$\Pi = \lambda\Sigma w_{mkt} = \mu + \varepsilon_\Pi,\ \varepsilon_\Pi \sim N(0, \tau\Sigma)$$

where Π denotes the excess equilibrium return vector of technologies, λ denotes the risk-aversion coefficient, Σ is the covariance matrix of excess returns, and w_{mkt} is the market capitalization weight of technologies. In our model, the market capitalization weight of a technology means the proportion of the number of citations of a technology in the total number of citations of candidate technologies. Thus, it is used not as indicators of markets but as those of patent citations. Note that the risk-aversion coefficient acts as a scaling factor for the excess returns. The higher the coefficient is, the more the excess return per unit of risk. The true expected returns μ are unknown. However, the excess equilibrium returns can serve as reasonable estimates with confidence $\tau\Sigma$. A small τ implies high confidence.

Experts have specific views regarding the expected returns of some technologies, which are different from the excess equilibrium returns. Assume that experts have k views. Those are formally expressed as a k-dimensional vector q with

$$q = P\mu + \varepsilon_q,\ \varepsilon_q \sim N(0, \Omega)$$

where P is a $k \times n$ matrix representing the technologies involved in the views, ε_q is the error term vector representing the uncertainty in the views, and Ω is a $k \times k$ matrix expressing the confidence in the views. Each row of matrix P represents a single view. Positive weights are given to outperforming technologies while negative weights are given to underperforming technologies. The term Ω is a diagonal covariance matrix with zeros in all of the off-diagonal positions.

Having expressed the equilibrium excess returns and experts' views, we can combine these together. The method depends on the mixed estimation technique suggested by Theil (1971). We can stack two equations of Π and q in the following form.

$$\begin{pmatrix} \Pi \\ q \end{pmatrix} = \begin{pmatrix} I \\ P \end{pmatrix}\mu + \varepsilon,\ \varepsilon \sim N\left[0\begin{pmatrix} \tau\Sigma & \\ & \Omega \end{pmatrix}\right]$$

where I denotes the $n \times n$ identity matrix. Given this equation, we can update the equilibrium expected returns by calculating the generalized least squares estimator. The Black–Litterman-based expected returns that blend the market equilibrium with the views can be expressed as follows.

$$E(\mu \mid views) = \left[(\tau\Sigma)^{-1} + P'\Omega^{-1}P\right]^{-1}\left[(\tau\Sigma)^{-1}\Pi + P'\Omega^{-1}q\right]$$

Using this expression, we finally determine the weights of each technology in the portfolio and construct the technology portfolio to incorporate both patent data and the views of experts.

4. Empirical analysis

4.1. Background

An example company, S company, is going to head into the molecular amplification instrument market. S company has grown based on precision machineries including security solution and power systems, and thus has little technological capability for biological instruments. The company needs to identify key technologies and determine with due consideration to future returns and risks what technologies they intend to develop internally or to buy. This is a typical technology portfolio for a new business.

Internal experts reach a consensus for the technology portfolio, but the experts are not able to make others accept their suggestion. Many experts argue that the technological and market risks are not sufficiently considered. Some experts argue that quantitative data should also be used and analyzed.

S company must reconstruct its technology portfolio in a way that reflects these opinions. It considers both returns and risks in appropriate measure and also incorporates various views not only from research and development (R&D) experts, but from other experts as well. Our method is a good fit with all the various needs.

4.2. Patent citation forecasting

The technological hierarchy comprising the molecular amplification diagnosis instrument is shown in Table 1. Experts identified 30 technologies as candidates for the technology portfolio across three levels. The US Patent and Trademark Office database served as the source. A proprietary JAVA-based web-mining program was used for data collection because the number of patents was sufficiently huge that we could not collect all of the patent data manually. A total of 3,290 patents were obtained. Finally, a patent database was constructed with Microsoft Access (Microsoft Corporation, Redmond, WA, USA) after the patent documents were parsed based on structure. Patent documents include a variety of information, such as assignee and classification, while the data fields most relevant for this study are patent number, time of issue, and citation information.

Considering the frequency and amount of data, we designated the time unit as a quarter in the process of extracting citation information from the patent database. Considering that the development of molecular

Table 1. Technological hierarchy of an instrument for molecular amplification diagnosis

Number	First-level classification	Second-level classification	Third-level classification
M1	qrt-PCR	Multiple reference genes	
M2		RNA isolation	
M3		TRIzol extraction	
M4		Column-based purification	
M5		mRNA quantification	
M6		TAqMan method	
M7		cDNA	
M8		Laser capture microdissection	
M9		Real amplicon detection	
M10		Dual priming oligonucleotide	
M11		TOCE	
M12	Amplification	Target amplification	PCR
M13			TMA
M14			NASBA
M15			SDA
M16		Probe amplification	LCR
M17			CPT
M18			Invader assay
M19		Signal amplification	bDNA
M20			HC
M21			HPA
M22		Multiple amplification	DNA chip
M23			Bead-based technology
M24	Automation	Robotization	Detection
M25			Handling
M26		Automatic real-time PCR	Control
M27			Nucleric acid purification
M28			Quantification of gene amplification
M29			Viable cell count
M30			Getting antigen density

PCR, polymerase chain reaction; qrt-PCR, quantitative real-time polymerase chain reaction; TOCE, tagging oligonucleotide cleavage and extension.

amplification diagnosis instruments has grown since the year 2000, a patent citation matrix was constructed with patent numbers, technology groups, and issued dates for 40 quarters. The resulting 3,290 by 43 patent citation matrix is not reported in its entirety because of lack of space. Table 2 presents part of the patent citation matrix.

We forecasted the future number of citations for 30 technologies over the next 5 years. To this end, the future number of citations for individual patents was first derived after determining the forecasting method that most appropriately described citation patterns of the past. For any method, the upper limit of the number of patent citations for a technology is determined by a consensus of six experts including two patent attorneys, two R&D experts, and two market experts. The method of LAD was used as the estimation method, implying conservative forecasting. The future returns and risks of the 30 technologies were subsequently obtained based on the average and the variance of counts of future citations.

Eighteen technologies with an expected number of citations less than 10 were excluded. Using 12 technologies from M12 to M23, we calculated the annual rate of return of each technology, divided it by the average rate of return of the 12 technologies, and thereby derived the relative rate of returns. Risk is measured by the variance of the relative rates of returns of all patents in a technology. The future number of citations, relative rate returns, and risks are summarized in Table 3. Obviously, M12, M13 and M16 outperform other technologies in terms of

Table 2. Part of the 3290 × 43 patent citation matrix

Patent number	Technology group	Issued time	1	2	...	39	40
7888319	M1	37	0	0	...	0	0
7888019	M1	37	0	0	...	0	0
7888010	M1	37	0	0	...	1	0
...	...	...	...	...	...	...	...
7700278	M12	34	0	0	...	2	0
7700275	M12	34	0	0	...	1	0
7695915	M12	34	0	0	...	0	0
7691333	M12	34	0	0	...	1	2
7687280	M12	33	0	0	...	1	4
...	...	...	...	...	...	...	...
7884140	M24	37	0	0	...	0	1
7504452	M24	29	0	0	...	1	1

Table 3. Forecasts of patent citations and relative rate of returns

Technology	Future number of citations			Relative rate of returns			Average	Variance
	Year 1	Year 3	Year 5	Year 1	Year 3	Year 5		
M12	2.05	9.88	32.04	1.36	1.17	1.21	1.25	0.01
M13	1.22	6.17	30.54	1.02	1.22	1.85	1.36	0.19
M14	1.92	7.85	19.73	1.06	0.99	0.94	1.00	0.00
M15	1.89	7.08	16.38	1.05	0.90	0.86	0.94	0.01
M16	1.98	10.19	33.63	0.87	1.25	1.23	1.12	0.04
M17	0.89	2.98	5.50	0.99	0.81	0.69	0.83	0.02
M18	0.42	1.75	4.87	0.92	1.02	1.04	0.99	0.00
M19	2.40	11.81	39.61	0.84	1.19	1.25	1.09	0.05
M20	16.16	67.78	154.90	0.74	1.01	0.85	0.87	0.02
M21	0.52	1.81	3.51	1.14	0.85	0.72	0.90	0.05
M22	0.79	3.37	8.19	1.05	1.02	0.91	1.00	0.01
M23	0.44	1.05	1.22	0.97	0.58	0.43	0.66	0.08

returns. Regardless, the risks should be considered together. For instance, M13 has a larger variance, implying higher risk.

4.3 Black–Litterman approach to technology portfolios

The Black–Litterman approach to technology portfolios is utilized for the task of incorporating the views of experts into the citation-based analysis of returns and risks. The first step is calculating the excess equilibrium relative returns. As previously noted, the three components needed are the risk aversion coefficient, the covariance matrix of excess relative returns, and the market capitalization weight of technologies.

All the experts of S company reached a consensus that they would accept the risk to some extent for the sake of new businesses. Accordingly, the risk aversion coefficient was set to be 2. Typically, the risk aversion coefficient is less than 6. We then obtained the covariance matrix by using the future time series of the relative rate of returns, as partly shown in Table 3.

The final piece is the market capitalization weight of technologies. In finance, a market portfolio consists of all traded stocks. The proportion of each stock in a portfolio equals the market value of the stock divided by the total market value of all stocks and is defined to be the market capitalization weight. Similarly, for our technology portfolio, the market portfolio is composed of 12 technologies considered for the new business. Thus, the proxy measure of the market capitalization weight of a technology is the number of citations of a technology divided by the total number of citations of 12 technologies.

Using these components, we calculated the excess equilibrium relative returns shown in Table 4. Note that the values are relative values. A technology with a negative value means that it underperforms relative to the average return of 12 technologies.

Experts from various departments in S company expressed their views regarding the potential and the future of the 12 technologies. They reached a consensus on the next 5 years across five views, as shown below.

1. View 1: Target amplification technologies will grow more than 15% on average.
2. View 2: Target amplification technologies will outperform both probe and signal amplification technologies by more than 5% on average.
3. View 3: Polymerase chain reaction (PCR) amplification technology will outperform other target amplification technologies by more than 7%.
4. View 4: Among multiple amplification technologies, DNA chip technology will outperform bead-based technology by more than 15% on average.
5. View 5: For cancer research, hybrid capture (HC) will outperform high-power amplifier (HPA) by more than 25%.

Table 4. Annual volatility, market capitalization weight and excess relative returns

Technology	Variance	Market capitalization weight (w_{mkt}) (%)	Excess equilibrium relative return (Π) (%)
M12	0.01	6.67	–1.07
M13	0.19	3.99	1.55
M14	0.00	6.25	–0.43
M15	0.01	6.17	–0.85
M16	0.04	6.44	2.12
M17	0.02	2.91	–1.10
M18	0.00	1.36	0.57
M19	0.05	7.82	2.05
M20	0.02	52.70	1.46
M21	0.05	1.68	–1.74
M22	0.01	2.59	–0.24
M23	0.08	1.43	–2.31

View 1 is an absolute view on four target amplification technologies from M12 to M15. In Table 5, the first row represents four technologies involved in View 1. We divided the market capitalization weight of each technology by the total market capitalization weight of four technologies and calculated the weight of each technology in matrix P.

The other views are relative views. We determined the weights of the other views such that they added up to zero. Positive weights were assigned to outperforming technologies and added up to 1. Negative weights were given to underperforming technologies.

Q is a view vector representing the results. The remaining component is the error term vector denoted by ε_q. It does not directly enter the formula. Instead, the variance of each error term, which is the absolute difference from the error term's expected value of zero, is put in the formula.

Table 6 shows the matrix Ω where variances of error terms were put in diagonal positions. Note that variance is a measure of confidence on views. Experts placed the most confidence on View 1, and the least confidence on View 5.

Combining the views of experts with the expected returns and risks based on patent citation, we calculated the newly combined returns and weights of 12 technologies as shown in Table 7. It is notable that the expert views significantly affect the relative returns. For instance, Views 4 and 5 expect that M20 (HC) and M22 (DNA chip) will outperform M21 (HPA) and M22 (bead-based technology), respectively. The results show that the combined returns of M20 and M22 increase, but the returns of M21 and M23 are reduced.

Taking together the combined returns and risks measured by covariances, the Black–Litterman model assigned new weights to the technologies. In Table 7, the target amplification technologies from

Table 5. Views of experts

P												Q
0.32	0.31	0.20	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.15
0.32	0.31	0.20	0.17	–0.13	–0.02	–0.02	–0.16	–0.62	–0.01	–0.03	0	0.06
1.00	–0.45	–0.30	–0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0	0.07
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	–1	0.15
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	–1.00	0.00	0	0.25

Table 6. Variances of error terms

Ω				
0.0070	0.0000	0.0000	0.0000	0.0000
0.0000	0.0196	0.0000	0.0000	0.0000
0.0000	0.0000	0.0323	0.0000	0.0000
0.0000	0.0000	0.0000	0.0311	0.0000
0.0000	0.0000	0.0000	0.0000	0.0669

Table 7. Black–Litterman excessive returns and weights

Technology	Excess equilibrium relative return (Π) (%)	Combined Black–Litterman return E (μ/*views*) (%)	Black–Litterman weights (%)
M12	–1.07	–2.35	35.06
M13	1.55	25.70	12.09
M14	–0.43	–3.13	7.44
M15	–0.85	–4.24	19.26
M16	2.12	7.10	
M17	–1.10	–7.61	4.25
M18	0.57	2.71	
M19	2.05	2.32	
M20	1.46	2.50	11.69
M21	–1.74	–10.22	
M22	–0.24	4.56	11.69
M23	–2.31	–12.83	

M12 to M15 occupy more than 70% of the complete technology portfolio. Views 1 and 2 strongly support these technologies. View 3 highly appreciates M12 (PCR). Obviously, these expert views increase the shares of target amplification technologies in the optimal portfolio constructed for S company. The shares of M20 and M22 are slightly above 20% because Views 4 and 5 identify some future potential for these technologies.

Technologies M17 (CPT) and M18 (invader assay) are capable of both target and probe amplification, and thus are influenced by Views 1, 2, and 3. Although the return of M18 is better than the return of M17, technology M17 is selected for the portfolio due to lower risk.

At first, S company experts constructed the technology portfolio qualitatively. The main difference in comparison to our Black–Litterman portfolio is that technologies that were excluded from our portfolio accounted for 25% of the original expert-based portfolio. Those types of technologies, characterized by little future return and potential, would have to be acquired by technology transactions in order to be efficient for a new business. Also in the original qualitative portfolio, the target amplification technologies occupy less than 50% of the portfolio, but M22 gets twice the weight, reaching up to 23%. This incongruity is evidence that experts can be inclined to prefer certain technologies without taking into account quantitative returns and risks. S company experts examined our Black–Litterman portfolio and made a consensus that they overestimated M1, M2, M5, M7, and M22 while underestimating M13, M15, and M20. The structural validity of our portfolio is confirmed by experts. However, our method needs to be validated by actual R&D or financial performance.

5. Discussion and conclusion

From an academic perspective, the primary contribution of this paper is to make technology portfolios more robust. An integration of nonlinear patent citation forecasting and the Black–Litterman portfolio method makes it possible to construct future-oriented technology portfolios with due regard to both quantitative data and expert judgments. Nonlinear patent citation forecasting enables us to calculate the future returns and risks of any technology, overcoming the time-lagging weakness of patent data alone. Our method for technology portfolios relies not only on historical data, but also on future-projected trends, and thus our portfolios are future oriented.

The strongest feature of the Black–Litterman portfolio is to improve the accuracy of inputs by combining the views of experts with quantitative data, which in this research is patent citation data. Patent citation data has many weaknesses, such as time lag and quality variation, among other flaws. Likewise, the judgments of experts are not always accurate primarily because the experts are not likely to have a detailed understanding of all technologies. Our approach is a solution that utilizes the advantages of both methods while minimizing weaknesses.

From a practical standpoint, our method provides corporate managers with balanced views on their technology portfolios, thereby avoiding the lopsided decisions to which some internal or external experts are inclined. Especially with regard to new businesses, internal experts have little knowledge about new emerging technologies. Also, external experts cannot know with certainty the extent of the technological capabilities of any given firm. Our approach has potential beyond the judgments of both types of experts, making any firm's new business technology portfolio robust and effective under severe conditions of future uncertainty. Put simply, high technology-based new businesses can be easily launched and boosted as long as the right technology portfolios are constructed. In practice, however, many decision makers tend to doubt the future success of new businesses because of ambiguous key technologies and products. In this regard, our method helps decision makers understand what are key technologies, and further, our method highlights the extent to which these key technologies will last over the future time horizon.

Despite contributions, our method has several limitations. Above all, market risks are not considered enough. Although the number of patent citations can be used as an indicator of market value and risk, it alone is not sufficient to measure market risk. Thus, a better way of measuring and using market risk should be investigated. Another problem is that the average number of patent citations should vary significantly with technologies. Thus, it is necessary to develop robust technology portfolio methods even if heterogeneous technologies are considered. Also, patent citations are good measures of relationships among technologies but could not identify some important technology interdependence. Some complementary measures will be of great help. Last but not least, the actual performance of our method needs to be validated through extensive application by technology portfolio developers and managers.

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