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Risk Analysis: Changing the Story with the Statistical Stochastic Process and VaR

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Abstract: With the dramatically increased demand for data analysis, statistical techniques play a key role in modern society for both academics and practitioners. Statistical techniques have been evolving from descriptive statistics to statistical inference in fields that require the evaluation of uncertainty and the quantification of risks. With the growing complexity of various fields, such as manufacturing and industrial applications, as well as business decision-making, modeling and quantifying risks has become essential. In this paper, we aimed to use statistical risk analysis and Value at Risk (VaR) to address the decision problem for project portfolios. Traditional economic evaluation criteria used in the management of project portfolios, as they pertain to new product development (NPD), are based on the assumption that pinpoint estimations will remain constant in the future. The assumption that NPD is static, however, is clearly unrealistic due to the inherent uncertainty of NPD projects. In this study, we stress the critical role that uncertainty plays in the selection of NPD portfolios, and clarify the reasons why it must not be overlooked. Using Value at Risk measurements, we show how uncertainty plays a critical role in evaluating and prioritizing NPD portfolios. The implications of this study regarding statistically modeling NPD portfolio decisions are provided for academics and practitioners.

Keywords: statistical risk analysis; stochastic process; uncertainty; Value at Risk (VaR)

MSC: 60G70

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Citation: Wu, L. Risk Analysis: Changing the Story with the Statistical Stochastic Process and VaR. *Axioms* **2023**, *12*, 418. https://doi.org/10.3390/axioms12050418

Academic Editor: Stelios Zimeras

Received: 30 March 2023
Revised: 18 April 2023
Accepted: 19 April 2023
Published: 25 April 2023

1. Introduction

New product development (NPD) project portfolio management has been recognized as one of the most important issues pertaining to managerial performance [1–5], with a profound impact on the success of business ventures [6–12]. It is estimated that billions are spent on NPD every year, and this figure is growing at an accelerated pace [13].

Given the prominence of NPD and limited organizational resources, industries are eager to learn how to prioritize their NPD portfolios [14,15]. Traditional methods employed in the management of NPD portfolios emphasize the importance of static economic analysis, such as NPV, discount flow, IRR, and payback period. The theoretical underpinnings of the traditional approach are predefined according to static analysis, assuming that everything remains unchanged for the duration of the entire project, and the market operates without uncertainty.

A large body of research has shown that NPD processes fluctuate and are subject to enormous uncertainty in areas such as technical, organizational, and market acceptance [16–22]. An obvious gap exists between the two philosophies. From this apparent dichotomy, we derive certain research questions: "Is it reasonable to expect to manage NPD portfolios with no regard for uncertainty?" and, "If not, what role does uncertainty play in the management of portfolios as it pertains to the development of new products?" In this study, we aimed to answer these questions. We employed the Value at Risk (VaR) concept to quantify uncertainty. By comparing the differences between traditional wisdom and treating NPD as a risky process, we showed that uncertainty is a critical aspect of managing portfolios for the development of new products, which no organization can afford to overlook.

2. Literature Review

New product development (NPD) has become a key issue in corporate success in the biochemistry industry, with increasingly significant contributions to sales and profits [23–26]. Despite the importance of NPD, the failure rate of newly developed products is surprisingly high [27,28], with reports of failure rates over 75% [29]. The cost of such failures is substantial for the companies involved, and a failure to manage NPD portfolios can lead to major losses for biochemistry companies.

The high failure rate in biochemistry NPD is a result of the uncertainty inherent in the biochemistry NPD process. Biochemistry new product development (NPD) projects are subject to the verdicts imposed by market demand, making them high-risk endeavors [30]. The low probability of technical success, high developmental costs, and uncertain market impact [31] combine to increase the risk and uncertainty in NPD. Picaud-Bello, Johnsen et al. [32] indicated that NPD is a dynamic process, while it has been argued that uncertainty is an inevitable part of the NPD process [33–35]. The literature has long documented the influence of uncertainty in NPD. For example, Song and Montoya-Weiss [36], as well as Krishnan and Bhattacharya [37], emphasized technological uncertainty in NPD success, while Ogawa and Piller [38] discussed uncertainty in the commercialization of new products. They argued that uncertainty accompanies the launch of new products, and companies often suffer from sales that fall notoriously short of the forecasts originally predicted by top managers in their NPD evaluation. Chiu, Hu et al. [39] emphasized the importance of risk in projects, and pointed out that projects often face bottlenecks and risks that can delay or lead to failure of these projects.

Financial methods have been the main criteria used for prioritizing NPD portfolios, and are the most commonly used methods for the management of NPD portfolios [37,40–45]. In a recent survey, financial methods were also the main criteria for NPD project selection [46,47]. It is not surprising that financial methods dominate the management of NPD portfolios. According to statistics, most businesses employ financial approaches in the management of their portfolios for project rating and ranking [48].

Traditional financial methods, such as discounted cash flow models, return on investment, and payback analyses, are static [49]. The expected returns of projects are predefined and assumed to remain unchanged, and these are used to rank the order in the portfolio. However, studies have long identified the potential risks in following traditional wisdom such as this. For example, Lint and Pennings [50] argued that NPV can only be used if NPD processes are static. They also stressed that risk assessment is an unquestionably important part of the NPD process. Davis [51] criticized accounting-based approaches for not properly considering uncertainty or project flexibility. He argued that most companies evaluate investments in new product development using accounting-based metrics that seldom reveal inherent risk [51]. Blau, Pekny et al. [52] also argued that static portfolio management is based on expected values of uncertain parameters, preventing it from revealing quantitative details associated with the NPD process.

In line with this research, a number of studies have begun considering the role that uncertainty plays in NPD portfolio management. [50] used the Real Options concept to demonstrate uncertainty and flexibility in NPD projects. They argued that although much has been written about NPD, relatively little has been written about incorporating uncertainty. Blau, Pekny et al. [52] used a different method to show the importance of uncertainty in NPD portfolio management. They proposed a two-dimensional chart listing uncertainties and values for use as a portfolio management tool. This chart enables managers to recognize uncertainty in determining resource allocation. Another stream in the management of NPD portfolios considers multi-dimensional items in which other factors are considered in NPD portfolio management; for example, the application of fuzzy logic [53] and neural network applications [54].

Nevertheless, the economic dimension employed in these models is also static. Bardhan, Sougstad et al. [55] examined the relevance of real options for valuing and prioritizing a portfolio of IT projects. They developed an options model that considers project interdependencies and provides insights into the business value of IT infrastructure projects. Mikaelian (2009) discussed the use of real options to capture flexibility, and Oehman et al. (2010) discussed the application of real options in NPD and emphasized the importance of uncertainty in NPD projects. Marmier et al. (2013) more directly indicated that NPD benefits are not static and are subject to change over time. Thangamani [56] argued that owing to the importance of risks, a simulation model for the risks embedded in projects is desirable.

Researchers have studied NPD portfolios based on multi-perspectives. For example, Cooper et al. (1997a, 1997b, 1999, 2001) proposed the alignment of management fit with NPD portfolios, and Salgado et al. (2012) incorporated hierarchical factors in NPDs. Shankar et al. (2013) emphasized the importance of collaboration and knowledge retained during the NPD process, while Markham et al. (2013) explored the role of uncertainty in NPD portfolio management. In recent decades, NPD project management, the concept of ex-ante communication, risk identification, and ongoing monitoring and reviewing have been proposed (Oehmen et al., 2010). This is defined as a risk management framework regarding ISO 31000. According to this framework, the importance of risk awareness in NPD projects aligning with a company's strategy, risk evaluation, and the nature of uncertainty is acknowledged. This framework indicates a direction towards rethink uncertainty and the nature of change.

Based on previous literature, we found that the major issues regarding the traditional approach to the management of NPD portfolios are the length of time required and inherent risk involved in the process. A static ex-ante evaluation such as NPV can leave gaps in the research findings regarding uncertainty. Nevertheless, the means by which the role of uncertainty in portfolio management can be explicitly described remain elusive, and their clarification is long overdue, despite having been intensively discussed and recognized as a problem. In the next section, we demonstrate the means by which uncertainty can be evaluated in the management of NPD portfolios, and we show how this differs from traditional wisdom in light of the Value at Risk (VaR) approach developed in the field of finance.

Value at Risk (VaR) was born of the increasing regulatory demand for quantitative risk management tools, resulting from the Asian financial market crash in 1987 and the disastrous losses resulting from derivatives trading of institutions such as Lehman Brothers Holdings Inc., American International Group, Inc. (AIG), Merrill Lynch, and the Long-Term Capital Management Fund. Value at Risk (VaR) has emerged as the most prominent means of measuring downside market risk [57]. It quantifies an upper bound on losses in terms of maximum loss exceeding the VaR, or the threshold with a target probability. Acknowledging the significance of VaR, several NPD studies have discussed VaR with regards to possible NPD evaluation. For example, Han, Kauffman et al. [58], as well as Benaroch, Jeffery et al. [59], discussed the possibility of describing how much the value of innovative NPD investment could decline over a given period of time, with a given probability, due to uncertainty. Browning [60] argued the importance of planning and tracking complex projects to account for uncertainty. He identified value and risk, and he urged the determination of a project's capabilities to meet goals and reduce value at risk. Guerra and Sorini [61] highlighted the potential of VaR methodologies for risk management decision making. Lucanera, Fabregat-Aibar et al. [62] identified variables that can cause business failure. They grouped high growth opportunities and accompanying risk measures, such as earnings and ROA. Jamshidnejad [63] proposed that models that can identify the necessary processes for risk evaluation are necessary in NOD. Zheng, Li et al. [64] discussed how market competition can lead to uncertainty, suggested that it is suitable for VaR analysis.

Despite awareness of VaR, there has been limited work using VaR in NPD evaluation. In the next section, we elaborate on how we used VaR and the means by which our proposed model statistically quantified the NPD process with regards to uncertainty.

3. A Statistical Risk Analysis under Uncertainty: Stochastic Process and Simulation

In this section, we show how uncertainty plays a critical role, and should therefore, not be overlooked, in NPD portfolio management. VaR is used to measure the risk that quantifies the potential loss that an NPD may experience over a given time horizon and at a certain level of confidence. The mathematical framework for VaR was based on the statistical distribution of the portfolio's returns.

Let X represent a distribution of profits and losses, where losses are negative and profits are positive. The VaR at a given confidence level α (where $\alpha \in (0,1)$) is the minimum value of y that results in the probability that Y: = $-$X (i.e., the negative of X) is bounded by y being at least 1-α. In summary, VaRα(X) is the (1-α)-quantile of Y, or in other words, the smallest value of y such that the cumulative distribution function of Y evaluated at y is greater than 1-α [65]. This can be expressed as

$$\mathrm{VaR}\alpha(\mathrm{X}) = -\mathrm{inf} x \in \mathrm{R} : \mathrm{F_X}(x) > \alpha = \mathrm{F}_{\mathrm{Y}}^{(-1)}(1-\alpha) \quad (1)$$

where $F_X(x)$ and $F_Y(y)$ are the cumulative distribution functions of X and Y, respectively.

There are different methods to calculate VaR, and traditionally, the most commonly used is the historical simulation method, which involves estimating the distribution of returns based on historical data.

To calculate VaR using historical data, the first step is to define the time horizon over which the VaR will be calculated. Next, the confidence level for VaR, such as 95% or 99%, is determined, while historical data are collected for the project returns over the specified time horizon, and the historical returns are sorted. The project value at the beginning and end of the time horizon for each historical return is calculated, assuming that the project is held constant over the period. Then, the loss for each historical return is examined by taking the difference between the project value at the beginning and end of the time horizon. Finally, to find the VaR, we identify the historical return at the chosen confidence level by taking the number of historical returns that exceed the VaR threshold and dividing by the total number of observations.

One such historical data-based formula is the Cornish–Fisher expansion, which is used to estimate the distribution of returns when the underlying distribution is not normal, but contains skewness and kurtosis. Skewness measures the asymmetry of the distribution, while kurtosis measures the degree of peakedness or flatness of the distribution. The Cornish–Fisher expansion [66] adjusts the normal distribution by adding or subtracting a skewness term and a kurtosis term, based on the actual values of skewness and kurtosis in the data.

The formula for VaR using the Cornish–Fisher expansion is

$$aR_\alpha = -\mu + z_\alpha \sigma + \frac{1}{6}(\gamma_1 - 3) z_\alpha^3 \sigma^3 + \frac{1}{24}\left(\gamma_2 - 5\gamma_1^2 - 4\right) z_\alpha^4 \sigma^4 - \frac{1}{36}\left(\gamma_1^3 + 3\gamma_1\gamma_2 - 6\gamma_3 - 2\gamma_1^2\right)\sigma^6 z_\alpha^6 + \cdots \quad (2)$$

where μ is the mean of the portfolio returns, σ is the standard deviation of the portfolio returns, γ_1 is the skewness coefficient, γ_2 is the kurtosis coefficient, z_α is the critical value of the standard normal distribution at the desired confidence level α, and the terms following the fourth term are higher-order terms that can be ignored for practical purposes.

In summary, this formula takes into account the non-normality of the distribution of returns and provides a more accurate estimate of VaR for portfolios with skewness and kurtosis. However, it requires estimating the skewness and kurtosis of the NPD project returns, which can be challenging and may require a large amount of historical data.

However, the historical data method is not applicable for projects that do not contain actual market data and the distribution of returns. In this case, the Monte Carlo simulation was applied to calculate VaR in our study. The Monte Carlo simulation is useful for estimating uncertain movements, particularly for projects with complex dependencies or non-linear relationships between projects [61]. The basic idea behind Monte Carlo simulation is to generate a large number of random scenarios for the project's returns for each scenario. The VaR estimate is then based on the losses associated with the worst-case scenarios at a given confidence level.

Because data regarding the development of new products involves business secrets, we used simulation techniques to obtain value paths. In light of VaR in the field of finance, the uncertainty involved in NPD was modeled and quantified (see Figure 1). In Figure 1, with an initial value at time t = 0, the shadow varied across the entire duration of the project. Different paths represent possible value paths subject to uncertainty that cannot be predicted during the initial evaluation stage. The paths were generated by a Monte Carlo simulation run over 10,000 times. The shadow area in Figure 1 shows the unfavorable possible paths of NPD values. The tail represents possible losses, insofar as the VaR level in Figure 1 represents the VaR value for Value at Risk under a 95% level of confidence.

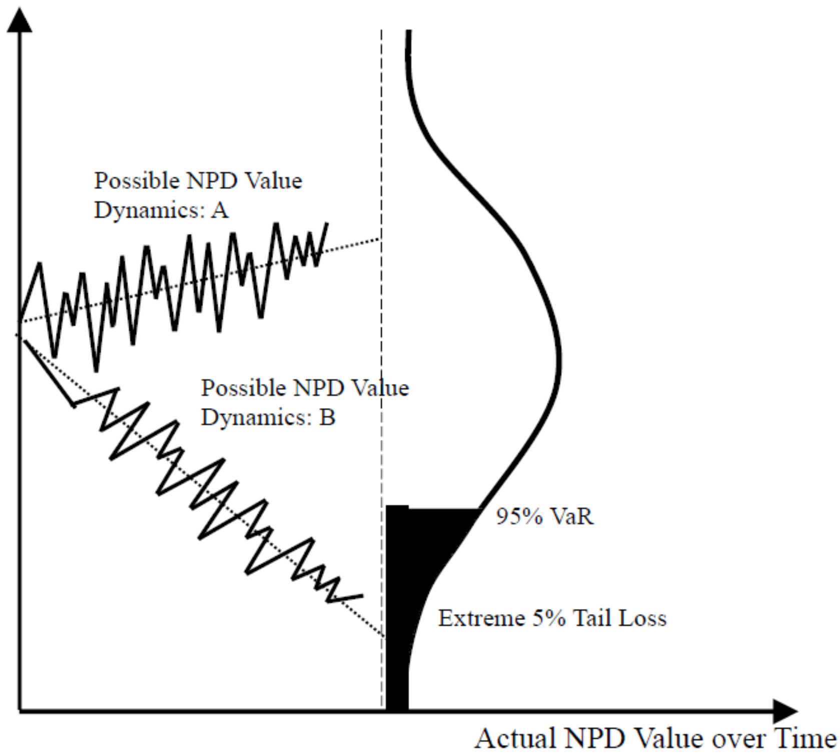


Figure 1. Value at Risk (shadow area) for the actual project value. Broken line: The trends for possible dynamics. Dotted line: The normal distribution.

A case is studied in which a company is considering five NPD projects, with predicted parameters prepared by top managers, ready to be used for inputting the net present value analysis, as listed in Table 1. In Table 1, the expected revenue was used, as in an NPV analysis. Risk is also considered in our analysis. Risk evaluation methods have been well documented in various studies, including those based on similar projects [67]. Management expertise is another commonly used method for risk analysis [68]. Some methods break down risk into factors [69] in which risks are measured separately using the abovementioned methods. Moreover, Bardhan et al. (2004) proposed a method to estimate project risk based on different project scenarios, without resorting to historical data or ad hoc project-specific assumptions. It would be easy for managers to substitute their case numbers into our framework.

Table 1. Project decisions under traditional wisdom (in USD).

	Project A	Project B	Project C	Project D	Project E
Expected Revenues	\$5000	\$2000	\$3000	\$10,000	\$6000
Costs	\$4000	\$3000	\$2000	\$7786	\$4000
Net Present Value	\$1000	−\$1000	\$1000	\$2214	\$2000
Uncertainty Degree (Ignored in the NPV analysis)	50%	50%	50%	50%	80%
Priority Decision	3	5	3	1	2

Management estimated that Project A could yield USD 5000 in revenue. Subject to the uncertainty of market acceptance, management believed that fluctuations of 50% in estimated revenues could be expected. For state-of–the-art technology in Project E, management expected a great deal of uncertainty in future sales, despite the promise of higher returns, if successful. Using the most commonly used criteria for net present value analysis, Project D was the first pick, with the greatest net present value (USD 2214) generated. The priorities for resource allocation are listed in Table 1.

This scenario tells a different story. However, when we take uncertainty into account, value added analysis reveals a great deal more information regarding the management of the NPV portfolio. The geometric Brownian motion (GBM) model is a commonly used stochastic model for simulating asset returns in Monte Carlo simulations for VaR estimation. GBM assumes that the asset returns follow a log-normal distribution and are driven by a Wiener process (also known as Brownian motion), which is a continuous-time stochastic process with independent, normally distributed increments. The formula for GBM involves several parameters, including the initial asset price, the expected return, the volatility of returns, and the time horizon. By considering the possible paths for future revenue generated by simulations, we can see how the maximum possible loss for each project varies. Our approach in this research is detailed as follows. Uncertain future revenues were modeled on the Brownian stochastic processes widely used in finance [70] as

$$\frac{dR_t}{R_t} = \alpha_t dt + \sigma_t dz_1 \tag{3}$$

where R_t represents future revenues, and $\frac{dR_t}{R_t}$ is the movement of uncertain future revenues in a small amount of time t. α_t is the drift in the movement of revenue; σ_t is the volatility of the future revenues; and z_1 is a random variable whose probability distribution is normal. Formula (3) is the famous Brownian stochastic process, in which uncertainty is described with both "expected revenues" and "possible variance of revenues".

Looking closely at Formula (3), it is not hard to see that the former item "expected revenues" functions exactly the same as the traditional net present value approach. A failure to consider "possible variance of revenues", which describes uncertainty, would make NPV a static analysis, failing to illustrate the entire story of NPV project management under uncertainty.

A discrete geometric Brownian motion (GBM) model is a stochastic process that models the evolution of an asset's price over discrete time intervals [71]. However, NPD project models require a continuous GBM process to accurately model the behavior of the NPD projects. To convert a discrete GBM to a continuous GBM, Ito's lemma can be used. Ito's lemma is a mathematical tool used in stochastic calculus to find the differential of a stochastic process [72]. The continuous GBM formula expresses the change in the NPD project revenues over an infinitesimal time interval as a function of the expected return, volatility, and a random variable that follows a normal distribution, and this formula can be used to simulate the NPD project revenues over continuous time intervals.

In Formula (3), we have the stochastic process, dR(t), which represents the change in the asset price over an infinitesimal time interval, dt:

$$\mathrm{dR(t) = R(t + dt) - R(t)} \tag{4}$$

Expanding the right-hand side of the discrete GBM model and subtracting *R(t)*, we obtain

$$\mathrm{dR(t) = R(t) * \left(exp\left(\left(r - 0.5\sigma^2\right)\Delta t + \sigma\varepsilon sqrt(\Delta t)\right) - 1\right)} \tag{5}$$

To convert the discrete GBM to a continuous GBM using Ito's lemma, we need to find the differential of dR(t) and express it in terms of the GBM parameters. Ito's lemma states that for a function f(x,t), where x is a stochastic process and t is time, the differential df(x,t) is given by

$$\mathrm{df(x, t) = (\partial f/\partial t)dt + (\partial f/\partial x)dx + 0.5\left(\partial^2 f/\partial x^2\right)(dx)^2} \tag{6}$$

where $(\partial f/\partial t)$ and $(\partial f/\partial x)$ are partial derivatives of f with respect to t and x, and $\left(\partial^2 f/\partial x^2\right)$ is the second partial derivative of f with respect to x.

To apply Ito's lemma to dS(t), we consider the function

$$\mathrm{f(R, t) = ln(R)} \tag{7}$$

Taking the partial derivative with respect to R, we obtain

$$\partial \mathrm{f}/\partial \mathrm{R} = 1/\mathrm{R} \tag{8}$$

Taking the second partial derivative with respect to *R*, we obtain

$$\partial^2 \mathrm{f}/\partial \mathrm{R}^2 = -1/\mathrm{R}^2 \tag{9}$$

Substituting these derivatives into Ito's lemma, we obtain

$$\mathrm{df(R, t) = (\partial f/\partial t)dt + (\partial f/\partial R)dR + 0.5\left(\partial^2 f/\partial R^2\right)(dR)^2} \tag{10}$$

Substituting in *dR(t)* from the discrete GBM model and simplifying, we obtain

$$\mathrm{df(R, t) = \left[\left(r - 0.5\sigma^2\right)R/\Delta t + \sigma R\varepsilon sqrt(\Delta t)\right]dt + \sigma R\varepsilon d\varepsilon} \tag{11}$$

Dividing both sides by *dt* and rearranging, we obtain the continuous GBM formula:

$$\mathrm{dR/R = rdt + d\varepsilon} \tag{12}$$

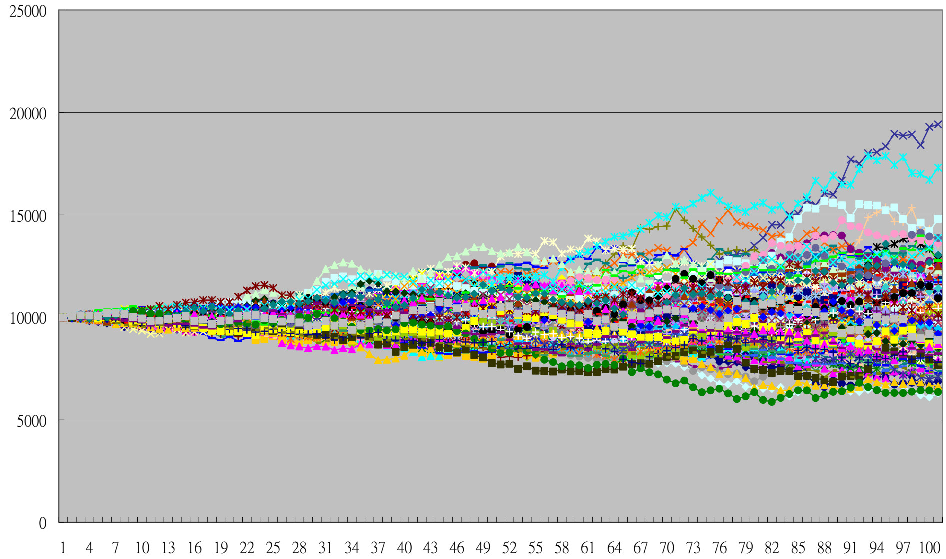
where dR/R represents the percentage change in the asset price over an infinitesimal time interval, dε is a random variable from a normal distribution with mean 0 and variance dt, and r and σ are the expected return and volatility of the asset returns, respectively.

Therefore, by applying Ito's stochastic calculus, Formula (1) can be expressed in a discrete term as

$$R_{t+\Delta t} = R_t e^{(\mu_t - \frac{1}{2}\sigma^2)\Delta t + \sigma_t \sqrt{\Delta t}\varepsilon} \tag{13}$$

where $R_{t+\Delta t}$ represents the increments of revenue over a very small period of time Δt. e is the nature log; μ is the drift of the revenue movement; σ_t is the volatility of the future revenues; and ε is a random variable whose probability distribution is normal.

Formula (13) is a closed-form discrete expression of uncertainty, forming the basis of our simulation. We simulated future revenue 1000 times for the five projects. By plotting all of the possible paths for future revenue, we can calculate the Value at Risk (VaR) under any level of confidence. To make our analysis more comprehensible to managers, we took Project D as an example. The pinpoint estimation of sales for Project D was USD 10,000. By using Formula (13) to list all possible unknown outcomes (see Figure 2), we found that for the worst scenario of VaR analysis under a 90% confidence level, the benefits can drop as low as USD 8256, rather than the pinpoint estimation of USD 10,000. By applying the same analysis for all five projects, we found that uncertainty plays a key role in NPD portfolio management. Pinpointing NPV analysis does not tell the entire story in cases of uncertainty, despite the fact that NPD projects are well documented and recognized as being rife with risk and beset with uncertainty.



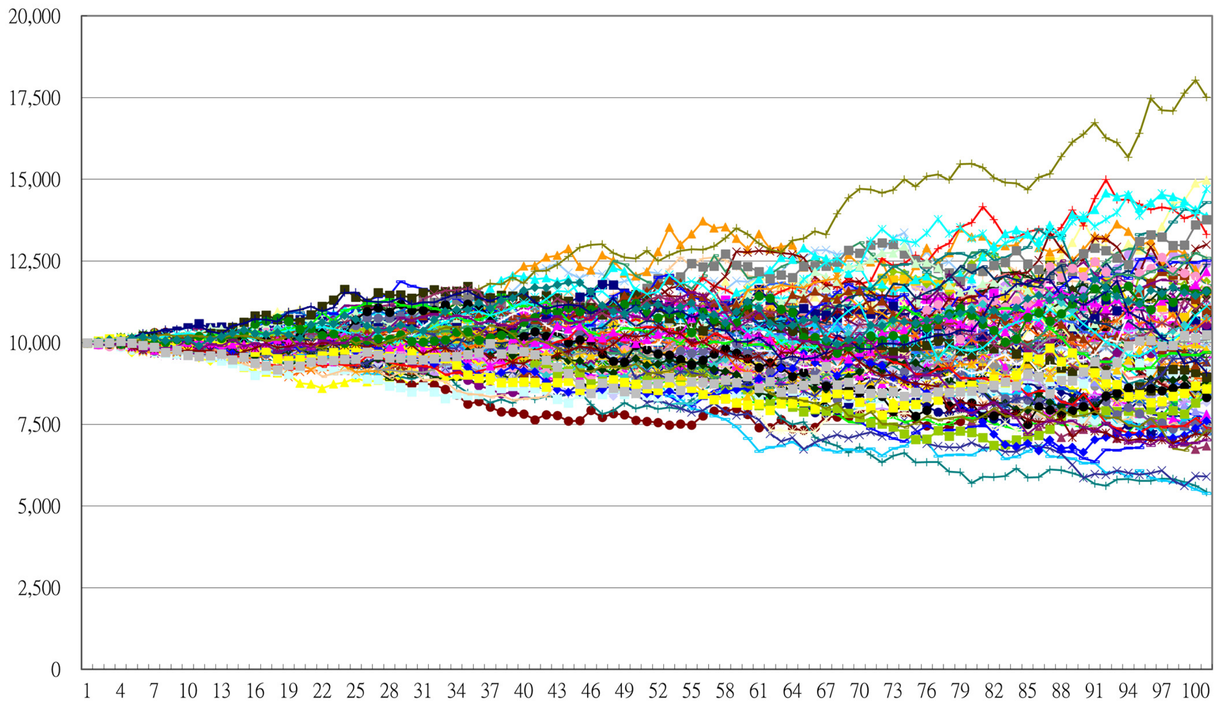
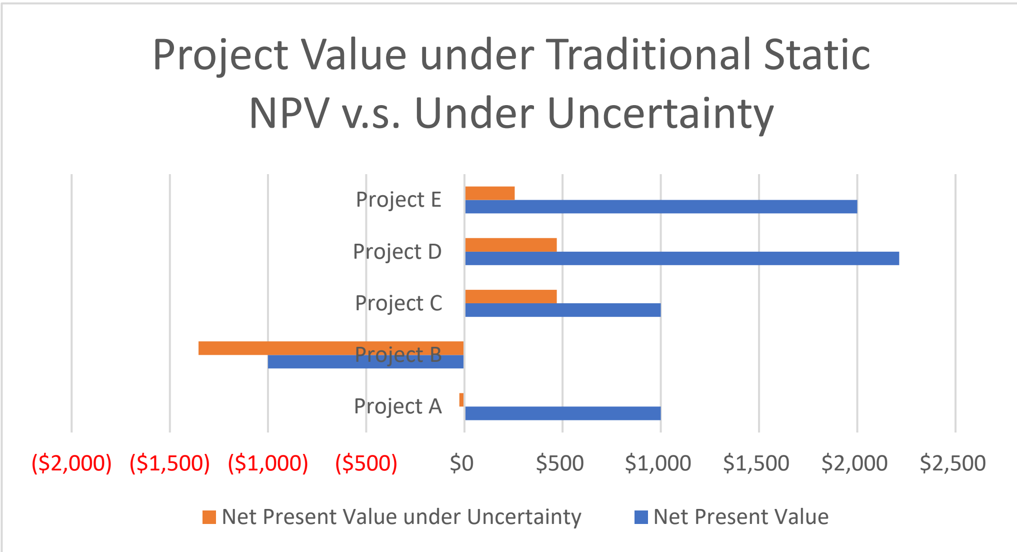


Figure 2. All possible paths of uncertain benefits of Project D. One color represents for one possible path. Figures stands for all possible paths of uncertain benefits of Project D.

Next, we list our results based on VaR analysis. The five competing NPD projects with limited organizational resources changed substantially, as shown in Table 2. Project C would be the first priority under the VaR because it brings the best NPV of USD 470, despite uncertainty. Project D, with the same value of USD 470, suffers from greater exposure to risk than Project C. The project value under traditional static NPV and that under uncertainty are compared in Figure 3.

Table 2. Project decisions taking uncertainty into account (in USD).

	Project A	Project B	Project C	Project D	Project E
Expected Revenues	$5000	$2000	$3000	$10,000	$6000
Uncertainty Degree	50%	50%	50%	50%	80%
Costs	$4000	$3000	$2000	$7786	$4000
Net Present Value	$1000	−$1000	$1000	$2214	$2000
Expected Revenues under Uncertainty (VaR 90%)	$3974	$1646	$2470	$8256	$4256
Monetary Exposed Uncertainty	−$1026	−$354	−$530	−$1744	−$1744
Net Present Value under Uncertainty	−$26	−$1354	$470	$470	$256
Return per Uncertainty Unit	−3%	−383%	88.7%	27%	15%
Decision under NPV	3	5	3	1	2
Decision under VaR	4	5	1	2	3



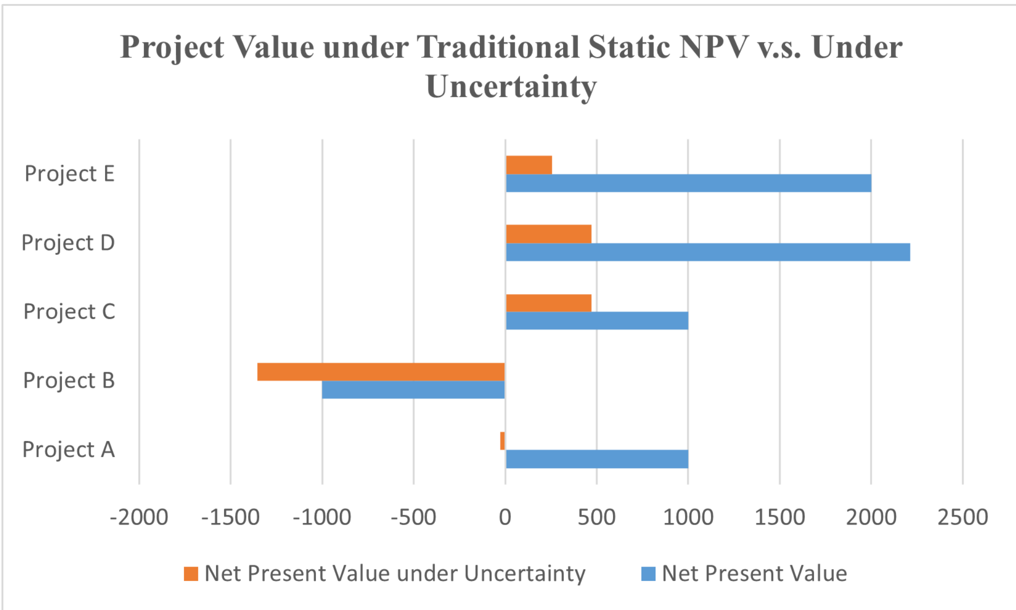


Figure 3. Project value under traditional static NPV vs. under uncertainty.

For the sake of clarity, we designed the Return per Uncertainty Unit item to clearly indicate the five projects in a climate of uncertainty. Project C, with the best return/risk evaluation, was the first choice, with limited organization resources. The ranking of the top four under static NPV analysis changed when taking uncertainty into account. Project B was obviously the worst project, and it should be discarded under both evaluation standards for projected revenues in an uncertain environment (−USD 1354), as it would be unable to cover the risk of future losses. For Project A, it would be risky for managers to undertake this project, because it could cause a negative NPV (under uncertainty) of −USD 26. Whether or not to undertake Project A would depend on the attitude of the managers toward risk (see Figures 4 and 5).

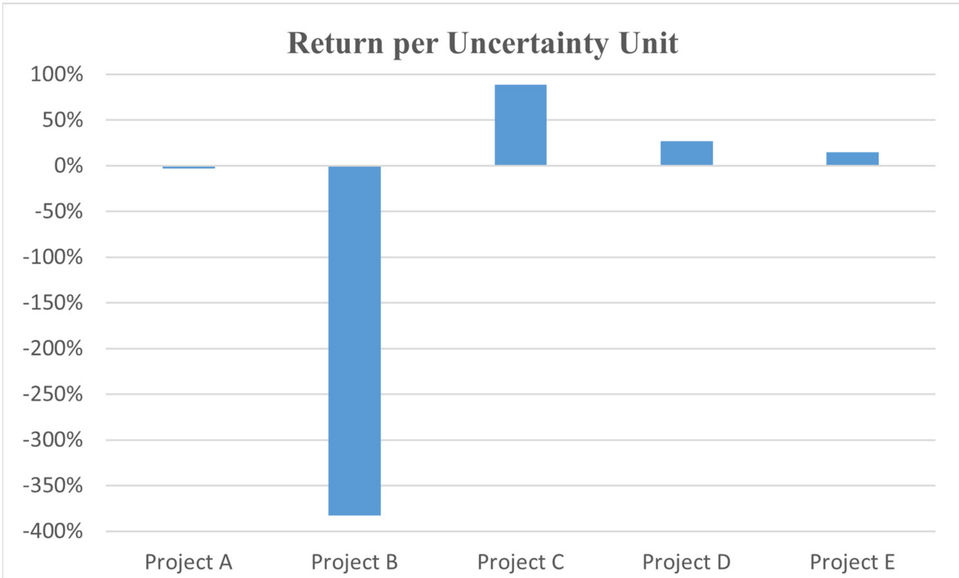


Figure 4. Return per uncertainty unit of the projects.

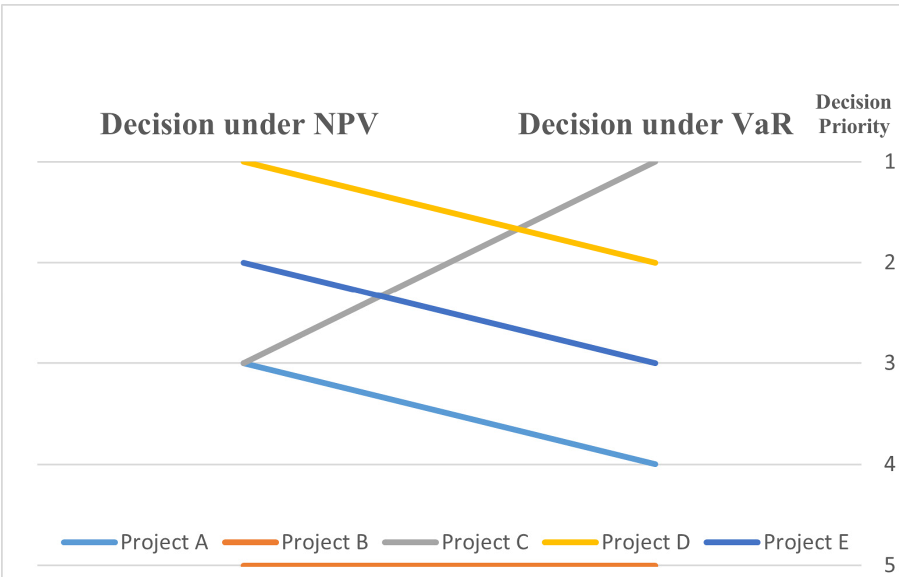


Figure 5. Changes in decision priority under uncertainty.

If the company wished to adopt the portfolios of Project C, Project D, and Project E, the entire uncertainty exposure in terms of monetary expression would be USD 470 + USD 470 + USD 1744 = USD 2684. Therefore, the company could use VaR as a tool for total risk management to deal with issues NPV fails to consider. In summary, under no uncertainty, the results are identical to those of traditional methods. The degree of the value gap between the conventional and the proposed model depends on the risks involved in the projects. An NPD portfolio carries risk and uncertainty and therefore, needs to be managed more effectively. Merely using pinpoint estimation does not tell the entire story. Our results showed that VaR, a long-missing element, should be considered in the management of volatile NPD portfolios for better decision making and the advantages of organizational competitiveness.

4. Conclusions and Managerial Implications

With the rapid development of society and technology, uncertainty and risks have become increasingly critical for project success. Top management has been confronted with the difficulty of managing NPD portfolios for significance and risk, and as a result, are pressured to prioritize their NPD projects with limited organizational resources. For project decisions, managers used to use conventional prioritization tools, such as project benefits. This is insufficient and can lead to destructive results. In this paper, we showed how uncertainty plays a critical role in evaluating and prioritizing NPD portfolios. We further statistically modeled risks in project decisions with uncertainty, and we quantified and evaluated risks inherent in uncertain projects. The results were surprisingly different (regardless of the risk) from those derived using traditional economic techniques for the management of NPD portfolios.

This study makes two significant contributions to the existing body of research in this area. First, despite the intense scrutiny that this field has attracted, uncertainty remains implicit in the management of NPD portfolios. There is a surprising scarcity of studies aimed at assessing how risk can be formatively described. This study fills this gap, and to the best of our knowledge, it is the first to use VaR to enrich the field of managing NPD portfolios. Second, although the literature on the management of NPD portfolios has been expanding as interest in this area intensifies [27,40,73,74], an informative framework providing effective guidance has remained elusive. The methodology of the prioritization scheme introduced in this study shows promise as a supplement to the traditional view of econometric techniques used to manage NPD projects. This could directly help with the evaluation and selection of new products to develop, and enable the sequencing or scheduling of the projects once they have been chosen.

Practitioners in the field can also benefit from our study. First, NPD is one of the most important activities in the decision-making processes that is crucial to the survival of a company. We showed how VaR encompasses the entire story for the consideration of those involved in the decision-making process. Second, the use of simple mathematics helps project managers to fully comprehend the ideas behind this approach, enabling them to integrate it into their managerial duties. Third, we designed the systems to employ monetary forms for the interpretation of results, which is essential for project managers. In practice, monetary expression is the language of management. Future directions were explored, including the use of cases in specific industries and the exploration of different Monte Carlo simulations.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

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