Technology Adoption Decisions under Uncertainty: Impacts of Alternative Return Assumptions on Timing of Adoption

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1. Introduction

There has been considerable interest in applying the financial option value theory to real investment decisions. A number of theoretical models have been developed to analyze the impacts of irreversibility and uncertainty on firms' investment decisions. The main conclusion from these models is that sunk investment costs with the combination of uncertainty in returns and flexibility in investment timing are important determinants of investment decisions (McDonald and Seigel, 1986; Dixit and Pyndick, 1994). The presence of these characteristics in investment decisions is shown to alter the traditional net present value rule (NPV) by including the "option value" of delay as a cost of investment. On the one hand, studies on investment under uncertainty have shown the importance of uncertainty in returns and sunk investment costs on firms' investment decisions, the extent to which these factors impact firms' investment decisions largely depends on the nature of stochastic processes used in deriving firms' investment rule. This paper examines the extent to which alternative stochastic processes have impacts on investment decisions of agricultural technologies. Two stochastic processes, geometric Brownian motion (GBM) that is a non-stationary stochastic process and mean reversion (MR) that is a stationary process, are commonly used to model returns of investment or output prices in the option value models.

A growing body of literature has recently applied the option value framework to analyze the timing of adoption of agricultural technologies under uncertainty. The value of investment opportunity that reflects the importance of uncertainty and irreversibility of investment on investment decisions was shown to be very high and the farmers would delay investment decisions as opposed to the NPV rule (Purvis et al.,1995; Winter-Nelson and Amegbetto 1998;

Price and Wetzstein, 1999; Khanna et. al, 2000). All these studies, however, assume that the return of investment or the price of output follows a GBM stochastic process. The main motivation for these studies to model the returns of investment as the GBM process is that it leads to tractable solutions for investment decisions. However, as demonstrated by a number of studies, the GBM process may not be a plausible equilibrium return process since the return of investment is unbounded above (Lund, 1993; Metcalf and Hassett, 1995). Although using this stochastic process in option value models is appealing because of its tractability, it may constitute an overly restrictive and unrealistic assumption in especially modeling agricultural investment decisions. This is because of the possible supply response to a change in output prices. An increase in output prices creates incentives for new farms to enter and existing farms to expand their facilities, which leads to an output increase. This output increase will lead to a reduction in output prices and the value of the investment opportunity given demand curves are downward sloping. It follows that any shock on agricultural returns is expected to be temporary other than persistent. Hence, one could argue that while in the short run returns of investment fluctuate randomly up and down, it should be drawn back towards the marginal costs of production. This effect of returns on firms' investment decisions can be taken into account using a MR stochastic process in option value models.

The purpose of this paper is to analyze the extent to which alternative stochastic processes have impacts on firms' investment decisions of agricultural technologies under uncertainty. Using an option value model with two alternative stochastic processes of the returns of the investment, GBM and MR, it shows the extent to which the alternative assumptions about the returns of investment have impacts on decisions to invest in agricultural technologies. The paper illustrates how one could model agricultural investment decisions using the MR process while comparing the optimal investment rules obtained under the GBM process with those obtained under the MR process. It therefore examines the validity of the assumption of the GBM process for agricultural investment decisions, and evaluates the consequences of this assumption on farmers' investment decisions.

A few studies examined the implications of alternative return assumptions on firms' investment decisions. Metchal and Hassest (1995) analyzed the impacts of choice of the GBM process without drift vs. the MR process on aggregate investment. They found that the aggregate investment under the GBM process without drift and the MR process would not differ significantly. Although alternative return assumptions may not have significant impact on aggregate investment, the firm-level investment decisions would be significantly affected. This is because heterogeneous firms may respond to uncertainties differently due to varying productivity of new investment projects. Dias and Rocha (1999) examined the investment timing and value in Brazilian petroleum sector using mean reversion and jump process while Schwartz (1997) analyzed the stochastic behavior of commodity prices and implications for investment timings. It is found that the threshold to undertake the project is higher for the GBM process than for the mean reversion-jump process (Dias and Rocha, 1999) and for the MR process (Schwartz, 1997). The contribution of this paper lies on examining the impacts of alternative stochastic processes on real investment decisions of heterogeneous firms in agriculture and showing the extent to which these impacts vary across heterogeneous firms.

The framework developed in this paper is applied to farmers' investment decisions of precision technologies in agriculture[1]. These technologies make it possible for farmers to acquire detailed information about spatial characteristics of their fields and target fertilizer applications

[1] Precision technologies include diagnostic tools such as grid-based soil testing to gather information about soil conditions in the field and the variable rate technology that applies fertilizers at a varying rate on-the-go within the field to meet location specific needs.

to meet spatially varying needs. This has the potential to improve yields and/or reduce fertilizer costs (Babcock and Pautsch, 1998; Khanna et al., 2000; Thrikawala et al., 1999). Investment in precision technologies is suitable to examine the validity of the developed model at least for three reasons. First, the returns from adoption of these technologies vary across farmers due to the heterogeneous soil characteristics existing within the farm fields. Second, the returns are uncertain to farmers due to uncertainty about output prices. Finally, the current adoption rates of these technologies among farmers are relatively low (Khanna et. al, 1999).

The results from the numerical simulation suggest that it is very important to consider mean reversion in returns in evaluating investment decisions using option value models. The NPV rule induces investment too early, but the option value approach using the GBM process without drift induces investment too late when it neglects mean reversion in returns. Thus, studies that assume the return of investment in agricultural technologies follows the GBM process without taking into account drift in the expected returns would overestimate the value of the investment opportunity, and the magnitude of error one could make by using the GBM process when the returns follow the MR process would be substantially high. The next section presents the theoretical framework for a farmer's investment decision under alternative assumptions about stochastic processes of the returns of investment. Section 3 describes the numerical simulation model and data used in the model. The results of the simulation are summarized in Section 4 followed by the conclusions in Section 5.

2. Theoretical Model

We consider a risk-neutral farmer currently operating a field of A acres. It is assumed that the farmer has a discrete choice between two technologies: conventional application practices and precision technologies, denoted by superscript C and M, respectively. Unlike the conventional application practices that apply inputs uniformly across a field, precision technologies make it possible for the farmer to apply the inputs at a spatially varying rate across the field. Input choice with precision technologies is based on more information and fewer constraints on the application rate as compared to the conventional application practices. Thus, these technologies have the potential to increase farm profits by increasing crop yields and/or decreasing input costs, but require a sunk cost of investment (*K*). The potential returns of precision technologies over the conventional application practices depend on heterogeneous soil characteristics (*Z*) within the field and vary across heterogeneous farmers. The farmer is assumed to be a price-taker in the input and output markets.

The returns from both technologies are stochastic due to uncertainty about output prices. Output prices (*P*) are assumed to be changing over time and the farmer has expectations of these prices in the future. We denote the farmer's return from investment in precision technologies over the conventional application practices as $V_T(P,Z) = V_T^M(P,Z) - V_T^C(P,Z)$ at time *T*. Under the NPV rule, the farmer would invest in precision technologies at *T=0* if $V_0(P,Z) > K$ or the rate of return from investment in precision technologies is greater than the discount rate ρ.

Under uncertainty, the decision problem is to maximize the net returns from investment in precision technologies by choosing an optimal time *T* to invest as:

$$F(V) = \max_T E\left[(V_T - K)e^{-\rho T}\right]. \tag{1}$$

The solution to the maximization problem in equation (1) may require specification of a stochastic process for *V*. We use two alternative stochastic processes, the GBM process and the MR process, which *V* may follow to derive optimal investment rules and to compare the resulting investment rules.

Geometric Brownian Motion

We first assume that the return stream *V* evolves as a geometric Brownian motion:

$$dV = \alpha V dt + \sigma V dz \tag{2}$$

where α is the drift parameter; σ reflects the volatility in the drift parameter; and *dz* is the increment of a Wiener process with mean zero and unit variance. The decision problem is to maximize (1) with respect to (2). Use of dynamic programming reveals that the optimal time to invest in precision technologies occurs when (Dixit and Pindyck, 1994):

$$V_T \geq \frac{\beta}{\beta - 1} K \quad \text{where} \quad \beta = \frac{1}{2} - \frac{\alpha}{\sigma^2} + \sqrt{(\frac{\alpha}{\sigma^2} - \frac{1}{2})^2 + 2\frac{\rho}{\sigma^2}} > 1 \, . \tag{3}$$

The investment rule under the GBM process states that investment in precision technologies occurs whenever the return is greater than the cost of investment by a factor of $\frac{\beta}{\beta - 1} > 1$. We refer to this as the option value multiple and denote it as H^{GBM}. This multiple is a positive function of the growth rate, α, and the volatility of the growth rate in *V*, σ^V, and a negative function of the discount rate, ρ. Alternatively, this rule can be interpreted in terms of the rate of return required to invest in precision technologies. It requires the rate of return be at least $\rho \frac{\beta}{\beta - 1}$ in order to invest in precision technologies. Hence, the investment rule appears to be intuitive, easy to interpret, and tractable.

Mean Reversion

The second alternative for obtaining an investment rule is to assume *V* evolves as a mean reversion stochastic process. We consider the following mean-reverting process for the return stream:

$$dV = \eta\left(\overline{V} - V\right)Vdt + \sigma Vdz \tag{4}$$

where $\eta\left(\overline{V} - V\right)$ is the expected percentage change in V; $\overline{V}$ is the normal level of V, that is, the level to which V tends to revert or the expected long run average of the returns of V; and η is the rate of mean reversion in the percentage changes of V. If η equals to 0, the return stream V follows the GBM process without drift (i.e., $\alpha = 0$). Following Dixit and Pindyck (1994) but instead using dynamic programming, we solve the maximization problem in (1) subject to (4) to obtain the value of the option to invest in precision technologies as:

$$F(V) = DV^{\theta} H\left(\frac{2\eta}{\sigma^2}V;\theta,b\right) \tag{5}$$

where $H\left(\frac{2\eta}{\sigma^2}V;\theta,b\right)$ is the confluent hypergeometric function; $b = 2\theta + \frac{2\eta\overline{V}}{\sigma^2}$; and θ is the positive root to the equation $0.5\sigma^2\theta(\theta-1) + \eta\overline{V}\theta - \rho = 0$. The critical value at which it is optimal to invest in precision technologies V^* can be found numerically from (5) using the two boundary conditions that $F\left(V^*\right) = V^* - K$, and $F_V\left(V^*\right) = 1$. Numerical solution methods are available to obtain the parameters of the optimal investment rule, i.e., the critical value at which it is optimal to invest in precision technologies (V^*). The option value multiple under the MR process, H^{MR}, is obtained by dividing the critical value at which it is optimal to invest (V^*) to the cost of investment (K).

The magnitude of the option value multiples estimated under the GBM process, H^{GBM}, and under the MR process, H^{MR}, reveals the impacts of uncertainty in returns and irreversibility of investment on the farmer's investment decision of precision technologies. It also provides the information about how the option value multiples of the GBM process and the MR process differ across heterogeneous farmers. The relationship between H^{GBM} and H^{MR} depends on the parameters of the optimal investment rule such as the rate of mean reversion, drift parameter, and volatility in the drift. This is an empirical question, and we address that by developing a numerical simulation model.

3. Numerical Simulation

We now apply the developed framework to adoption of precision technologies in agriculture. The empirical analysis is based on the work of Isik et al. (2001). The empirical application considers variable rate applications of three fertilizer inputs (nitrogen, phosphorous, and potassium) applied to corn production under Illinois conditions on a 500-acre farm. The returns from investment in precision technologies over the conventional application practices were estimated under various heterogeneous soil conditions. The adoption of precision technologies makes it possible for the farmer to apply the fertilizers at a spatially varying rate across the field. This has the potential to improve crop yields and/or to reduce fertilizer costs and therefore to increase farm profits. Soil conditions (Z) on the field are characterized by two features – soil fertility and soil quality. Soil fertility is defined in terms of the levels of phosphorus and potassium in the soil. Soil quality depends on characteristics such as organic matter and the sand and clay content of soil. These characteristics determine the productivity of the soil and its maximum potential yield per acre under given climatic conditions. Detailed theoretical and empirical derivation of the potential returns of precision technologies, alternative distributions of soil fertility and soil quality, and the empirical specification of production function can be found at Isik et al. (2001).

Investment in precision technologies requires the fixed cost of investment in a package of technologies for variable rate applications of fertilizers. The technology package for precision technologies includes grid soil sampling and testing, a yield monitor with moisture sensors, a

GPS receiver, field marker, mapping software and variable rate application equipment together with the required application software for prescription for variable rate applications of fertilizers. Total cost of the technology package is about \$25,425 (\$10.2 per acre per year with a 5% discount rate) for a 500-acre farm in Illinois (Isik et al., 2001).

The stochastic nature of the quasi-rent differentials is assumed to arise from uncertainty in the output prices. Output prices are assumed to follow either the GBM process or the MR process. We first model the output price process as the GBM process represented by the following discrete approximation:

$$P_t = (1+\gamma)P_{t-1} + \lambda P_{t-1}\nu_t \qquad (7)$$

where γ is the drift parameter; λ is the standard deviation in the drift parameter; and ν_t is a random variable with mean zero and unit variance. The drift parameter is estimated as $\gamma = m + (0.5)\lambda^2$, where *m* is the mean of the series $\ln(P_{t+1}/P_t)$ and λ is the standard deviation of the series. Using the historical data on real corn prices over the period 1926-1998 (USDA, 1998), the value of γ is found to be -0.014. The standard deviation of the average annual percent change λ is estimated to be 0.223. We also model the output price process as a stationary process[2]. The price processes under the GBM process and under the stationary process (MR) are used to separately forecast prices for a 25-year period by assuming random shocks drawn from a standard normal distribution. These prices are then used to forecast the discounted quasi-rent differential, *V*.

A series of *V* is estimated for the 25 years under each of the alternative assumptions about the parameters of the soil fertility and soil quality distributions. For each of these series we then

[2] We estimate the following Ornstein-Uhlenbeck MR process: $dP = \eta[(\alpha_0 + \alpha_1 t - P) + \alpha_0]Pdt + \sigma P dz$. In discrete time, this process can be characterized by a bivariate AR(1) process.

estimate the parameters of the stochastic process of the returns to obtain the critical value at which it is optimal to invest in precision technologies and the option value multiples. Parameters of (4) are estimated for the per-acre returns of investment by running the following regression:

$$\ln(V_{t+1}) - \ln(V_t) = a + bV_t + \varepsilon_{t+1}. \tag{8}$$

The long-run average of the return V is then calculated from (8) as: $\bar{V} = -\hat{a}/\hat{b}$ while the mean reversion parameter η is estimated as: $\eta = -\log(1+\hat{b})$ (Dixit and Pindyck, 1994).

Numerical Method for Estimating the Option Value under the MR Process

The critical values of V at which it is optimal to invest in precision technologies and the option value multiples under the MR process are estimated using a numerical solution method. The solution algorithm requires approximation of the hypergeometric function up to *n* power and then finding the critical value at which it is optimal to invest by iterating values of V until the two boundary conditions are satisfied. The critical value at which it is optimal to invest is then obtained as follows. We first estimate the parameters b and θ in (6) from the series of the expected returns estimated. Using these coefficients and the two boundary conditions, $F(V^*) = V^* - K$ and $F_V(V^*) = 1$, the critical value at which it is optimal to invest (V^*) is obtained from the following equation:

$$1 = \frac{(V^* - K)\theta}{V^*} + \frac{(V^* - K)F}{G} \tag{9}$$

where G is the hypergeometric function which has the following series representation $G = 1 + \frac{\theta}{b}\left(\frac{2\eta V}{\sigma^2}\right) + \frac{\theta(\theta+1)}{b(b+1)2!}\left(\frac{2\eta V}{\sigma^2}\right)^2 + \frac{\theta(\theta+1)(\theta+2)}{b(b+1)(b+2)3!}\left(\frac{2\eta V}{\sigma^2}\right)^3 + \cdots$; and F is the derivative of G with respect to V. We use a Monte-Carlo simulation method to obtain V^* in (9). The values of

G as well as F converge to specific values as n gets larger. We obtained all the critical values using the series up to power 15.

4. Results of Simulations

We examine the implications of assumptions about the distribution of the returns of the investment for farmers' investment decisions in precision technologies. We estimate the expected returns of investment in precision technologies over the conventional application practices for the alternative distributions of soil fertility and soil quality within the field (Table 1)[3]. Using the expected returns of precision technologies over the 25-year period, we estimated the parameters of the optimal investment rule under the GBM process and the MR process. The results indicate that the returns of investment in precision technologies vary across heterogeneous soil characteristics represented by the alternative distributions of soil fertility and soil quality within the field. The drift parameters of the expected returns, which indicate the expected growth rate in the returns form investment in precision technologies over time, also vary across heterogeneous soil characteristics. The long run average of the expected returns is lower than the return at the initial year of the investment due to the declining trend in the real returns over time. This declining trend in the returns is because of the declining trend in the real corn prices. The estimated mean reversion parameter also varies across heterogeneous soil characteristics and is relatively small when the return of investment is high (Table 1).

Table 2 presents the option value multiples (H^{GBM} and H^{MR}) with the 5% discount rate for the alternative soil fertility and soil quality distributions under the GBM process with the drift, the GBM process without the drift and the MR process. The results show that the impacts of uncertainty in returns and irreversibility of investment on the farmer's invest decision in

[3] The expected returns were estimated assuming that the price process follows either the GBM process or the MR process. Because the generated expected returns under the GBM price process and under the MR price process do not differ significantly, we only report the returns generated under the GBM price process.

precision technologies differ under the MR process and the GBM process. The option value multiples estimated under the MR process (H^{MR}) are lower than those estimated under the GBM process without the drift for all the soil fertility and soil quality distributions considered here. Ignoring the mean reversion in the returns of investment in precision technologies would lead to overestimation of the option value multiples between 5.5% and 44.5% as compared to the levels under the GBM process without the drift depending on the distribution of soil fertility and soil quality within the field.

When we take into account the drift of the expected returns in the estimation, the option value multiples of the GBM process compared to those obtained with the GBM process without the drift decreased significantly, reducing the impacts of uncertainty in returns and irreversibility of investment on the farmer's investment decision. Thus, in most of the cases the option value multiples are higher under the MR process than those under the GBM process with the drift. This indicates that assuming that the returns follow the GBM process with the drift would underestimate the impacts of uncertainty in returns and irreversibility of investment on the farmer's investment decision if the returns followed the MR process. Assuming that the returns follow the GBM process with the drift leads to underestimation of the option value multiples between 11% and 31% on most of the soil distributions considered here while it leads to overestimation between 3% and 23% on other soil distributions considered if the returns follow the MR process (Table 2).

Impact of Discount Rate on Option Value Multiple

We also examine the impacts of an increase in the discount rate on the option value multiples under both the GBM process and the MR process. An increase in the discount rate from 5% to 10% leads to a decrease in the option value multiples under both the GBM process and the MR process for all the soil fertility and soil quality distributions considered here. For example, the estimated option value multiple for the low quality soil with 25% coefficient of variation and 45% coefficient of variation in soil fertility distribution under the GBM process without the drift decreased from 2.772 to 2.414 while it decreased from 2.162 to 2.147 under the MR process.

Impact of Long-Run Average of Returns and Mean Reversion Parameter

The long-run average of the expected returns of the investment in precision technologies impacts the option value multiples differently under the GBM process and under the MR process. An increase in the long run average of the expected returns leads to an increase in the option value multiples under the MR process, making waiting to invest in precision technologies in the future more profitable. For example, an increase in the average return of the low quality soil with 25% CV and 45% CV in soil fertility distribution from 14.86 to 24.86 increased the option value multiple from 2.162 to 3.145. On the other hand, an increase in the average return does not affect the option value multiples under the GBM process. This is because the GBM process does not take into account the long run average of the expected returns in the estimation of the option values.

The mean reversion parameter also has impact on the option value multiples obtained with the MR process. A decrease in the mean reversion parameter leads to an increase in the option value multiples for all the soil fertility and soil quality distributions considered here. For example, a decrease in the mean reversion parameter for the low quality soil with 25% CV and 45% CV in soil fertility distribution from 0.0334 to 0.0134 increases the option value multiple from 2.162 to 2.223. When the mean reversion parameter is equal to zero, the option value multiple under the MR process is equal to that under the GBM process without the drift for this soil distribution.

5. Conclusions

The real options approach is gaining support for the theoretical and empirical applications of investment under uncertainty. This paper examines the implications of alternative assumptions about return distributions for the timing of investment in agricultural technologies. The numerical simulation model examines the extent to which the alternative distributional assumptions about returns have impacts on farmers' investment decisions in precision technologies. Using both the MR process and the GBM process, it estimates the option value multiples which reflect the importance of uncertainty in returns and irreversibility of investment on farmers' investment decisions.

The results show that the impacts of uncertainty in returns and irreversibility of investment on farmers' investment decisions differ under the MR process and the GBM process. The option value multiples under the MR process are lower than those under the GBM process without the drift. This indicates that assuming that the returns of the investment follow the GBM process without taking into account the drift parameter would overestimate the impacts of uncertainty and irreversibility on investment decisions. On the other hand, the GBM process with the drift in returns would underestimate the impacts of uncertainty and irreversibility on decisions to invest in precision technologies on most of the cases considered in this study if the returns follow the MR process. The impact of assumptions about alternative stochastic processes on decisions to invest in precision technologies varies across heterogeneous farmers.

The results suggest that it is important to consider mean reversion in returns in evaluating agricultural investment decisions under uncertainty and irreversibility using the real options approach. The NPV rule induces investment too early by ignoring uncertainty in returns and irreversibility of investment, but the option value approach deriving the optimal investment rule with the GBM process without drift induces investment too late when it neglects mean reversion in returns. The option value approach under the GBM process with drift, on the other hand, induces investment earlier than under the MR process on most of the cases. Studies that assume the returns of investment follow the GBM process without drift would overestimate the value of the investment opportunity while they would underestimate it if they assume the returns of investment follow the GBM process with the drift in returns. We found that the magnitude of error one could make by using the GBM process when the returns follow the MR process is substantially high.

Table 1. Parameters Used in the Numerical Simulation Model

		Parameters of Simulation Model[1]				
Soil Quality (CV)[2]	**CV of Soil Fertility (%)[2]**	V_0	$\overline{V}$	α	σ	η
LOW (25%)	30	14.5	10.54	-0.044	0.367	0.0473
	45	20.4	14.86	-0.051	0.407	0.0334
	60	24.4	17.67	-0.055	0.432	0.0285
LOW (40%)	30	22.4	16.75	-0.047	0.329	0.0315
	45	27.8	20.55	-0.044	0.331	0.0282
	60	31.3	23.30	-0.047	0.343	0.0224
HIGH (25%)	30	21.6	15.94	-0.059	0.378	0.0321
	45	30.5	22.46	-0.049	0.388	0.0258
	60	37.5	27.21	-0.051	0.398	0.0237
HIGH (40%)	30	29.0	21.84	-0.051	0.321	0.0251
	45	37.4	28.06	-0.043	0.331	0.0232
	60	44.2	32.56	-0.045	0.348	0.0213

[1]The values of V_0 and $\overline{V}$ represent the per-acre return at the year 0 and the per-acre long run average, respectively.

[2]CV referees to coefficient of variations. Low soil quality indicates an average potential yield of 130 bushels/acre. High soil quality indicates an average potential yield of 165 bushels/acre.

Table 2. Option Value Multiples under Geometric Brownian Motion and Mean Reversion

		Option Value Multiple[1]			% Overestimation in Option Value Multiple under	
Soil Quality (CV)[2]	**CV of Soil Fertility (%)**[2]	**GBM With Drift**	**GBM Without Drift η=0, α=0**	**MR**	**GBM With Drift**	**GBM Without Drift**
LOW (25%)	30	2.132	2.515	1.740	22.53	44.54
	45	2.236	2.772	2.162	3.42	28.21
	60	2.317	3.359	2.735	-15.28	22.82
LOW (40%)	30	1.909	2.714	2.407	-20.69	12.75
	45	2.029	2.729	2.518	-19.42	8.38
	60	2.335	2.822	2.625	-11.05	7.50
HIGH (25%)	30	2.019	3.107	2.436	-17.12	27.55
	45	2.087	3.192	3.024	-30.99	5.56
	60	2.167	3.289	3.116	-30.46	5.55
HIGH (40%)	30	1.854	2.654	2.450	-24.33	8.33
	45	1.937	2.729	2.559	-24.31	6.64
	60	1.939	2.862	2.700	-25.62	6.00

[1]5% discount rate is used in the estimation of option value multiples.
[2]CV referees to coefficient of variations. Low soil quality indicates an average potential yield of 130 bushels/acre. High soil quality indicates an average potential yield of 165 bushels/acre.

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