

Technical Uncertainty in Real Options with Learning[☆]

The Journal of Energy Markets, Forthcoming

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Abstract

We introduce a new approach to incorporate uncertainty into the decision to invest in a commodity reserve. The investment is an irreversible one-off capital expenditure, after which the investor receives a stream of cashflow from extracting the commodity and selling it on the spot market. The investor is exposed to price uncertainty and uncertainty in the amount of available resources in the reserves (i.e. technical uncertainty). She does, however, learn about the reserve levels through time, which is a key determinant in the decision to invest. To model the reserve level uncertainty and how she learns about the estimates of the commodity in the reserve, we adopt a continuous-time Markov chain model to value the option to invest in the reserve and investigate the value that learning has prior to investment.

Keywords: Real Options; Investment under Uncertainty; Technical Uncertainty; Irreversibility

1. Introduction

What are the optimal market conditions to make an investment decision is an extensively studied problem in the academic literature and a key question at the heart of the valuation and execution of projects under uncertainty. Some investment projects are endowed with the option to delay decisions until market conditions are optimal. This option is valuable because decisions are made when the potential gains stemming from the decision are maximized. The classical work of McDonald and Siegel (1986) is the first to formalize the investment problem

[☆]We are grateful to two anonymous referees for valuable comments.

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as a real option to invest in a project. In their work, the value O_t of the option is calculated by comparing the difference in the value of investing now and the value of making the investment at a future time. Specifically, the value of the real option is

$$O_t = \sup_{\tau \in \mathcal{T}} \mathbb{E} \left[e^{-\rho(\tau-t)} (V_\tau - I_\tau)_+ \right], \quad (1)$$

where \mathcal{T} is the set of admissible \mathcal{F} -stopping (exercise) times, ρ is the risk-adjusted discount rate, and V_t and I_t are the project value and (sunk) cost respectively. The project value and cost are traditionally modeled with a geometric Brownian motion (GBM). The solution to this problem shows that the optimal investment strategy is to invest when the ratio V_t/I_t reaches a critical boundary B (the problem of optimal scrapping/divesting is similar, with the roles of V_t and I_t reversed). More recently, several authors have studied this problem with mean-reverting project value and costs (see, e.g., Metcalf and Hasset (1995), Sarkar (2003), Jaimungal et al. (2013)).

In another classical paper, Brennan and Schwartz (1985) focus on the management of a mine (controlling output rate, opening/closing of mine, abandonment, and so on) rather than the optimal timing problem (see also Dixit (1989)). Management decisions are modulated by the output prices which are modeled as a GBM, while costs are known.

These classical works do not take into account the uncertainty associated with reserve levels. To account for such “technical uncertainty”, Pindyck (1980) develops a model where the demand and reserve levels fluctuate continuously with increasing variance. Furthermore, the optimal strategy is influenced by exploration and is introduced as a policy (i.e. control) variable in two distinct ways. The first allows exploratory effort to affect the level of “knowledge”, which reduces the variance of reserve fluctuations. The second assumes that reserves are discovered at a rate that depends on: how much has already been discovered in the past, the amount of current effort, and exogenous noise.

More recent approaches to the investment timing problem with technical uncertainty include those using Bayesian updating as in Armstrong et al. (2004), modeling project costs via Markov chains as in Elliott et al. (2009), and using proportionality to model learning as in Sadowsky (2005). Also, Cortázar et al. (2001) describes a comprehensive approach to valuing several-stage exploration, solving the timing problem, and provides investment management (closure, opening, etc.) decision rules – see also Brennan and Schwartz (1985). Other works that incorporate real option techniques in the valuation of flexibility and investment decisions in commodities and energy include that of Himpler and Madlener (2014) who look at the optimal timing of wind farm repowering; Taschini and Urech (2010) who look at the option to switch fuels under different scenarios and fuel incentives; the work of Fleten et al. (2011) that looks at the option to choose the capacity of an electricity interconnector between two locations, and Cartea and González-Pedraz (2012) who value an electricity interconnector as a stream of real options of the difference of prices in two locations. Meanwhile, Cartea and Jaimungal (2017) study the effect that model uncertainty has on irreversible investments.

This work adds to the literature by incorporating both market and reserve uncertainty, while allowing the agent to learn about the status of reserves. Reserve uncertainty is represented by a Markov chain model with transition rates that decay as time flows forward to mimic the notion of learning. The model setup is developed in the context of oil exploration, however, it may be applied to other investment problems in commodities, such as mining for precious or base metals, and natural gas fields. We value the irreversible option to invest in the exploration by developing a version of Fourier space-time stepping, as in Jackson et al. (2008), Jaimungal and Surkov (2011), and Jaimungal and Surkov (2013) for equity, commodity and interest-rate derivatives, respectively. For other work on ambiguity aversion and model uncertainty in commodities and algorithmic trading see Cartea et al. (2016), Cartea et al. (2017), Cartea et al. (2018),

If estimates on exploration costs and volume estimates are available, the calibration of the model is relatively simple. We demonstrate how the model can be used to assess whether exploration costs warrant the potential benefits from finding reserves and extracting them. Specifically, we show how to calculate the value of the option to delay investment and discuss the agent’s optimal investment threshold. This threshold, also referred to as the exercise boundary, depends on a number of variables and factors including: the agent’s estimate of the volume in the reserve, the rate at which the agent learns about the volume of the reserve, the rate at which the agent extracts the commodity, and the expiry of the option. We show that the value of the option to wait-and-learn is high at the beginning and gradually decreases as expiry of the option approaches because the agent has little time left to learn.

We assume that the investment cost depends on the volume of the reserve. If the estimated volume is high (resp. low) the sunk cost to extract the commodity is high (resp. low). This has an effect on the optimal time to make the investment as well as the level of spot price commodity that justifies making the sunk cost. For example, we show that when the volume estimate is low, and the option to invest is far away from expiry, the agent sets a high investment threshold as a result of two effects which make the option to delay investment valuable. First, low volume requires a high commodity spot price to justify the investment. Second, far away from expiry the investor attaches high value to waiting and learning about the volume estimates of the reserve. On the other hand, as the option approaches expiry, these two effects become weaker. In particular, the value of learning is low because there is less time to learn about the reserve estimates, so the investment decision is merely based on whether costs will be recovered given the spot price of the commodity, the rate at which the commodity is extracted, and the uncertainty around it.

The remainder of this paper is organized as follows. In Section 2, we provide the details of our modeling framework, including how we model both technical uncertainty and the uncertainty in the underlying project. Moreover, we provide an approach for accounting for the agent’s learning of the reserve environment through exploration. Next, Section 3 provides an analysis of the Fourier space-time stepping approach for valuing the early exercise features

in the irreversible investment with learning. Section 4 shows how the model can be calibrated to estimates of the cost of exploration and the expected benefits of this exploration. Section 5 provides some numerical experiments to demonstrate the efficacy of the approach and an analysis of the qualitative behavior of the model and its implications. Finally, we provide some concluding remarks and ideas for future lines of work.

2. Model Assumptions

In this section we provide models for the two sources of uncertainty that drive the value of the real option to explore and (irreversibly) invest in a project. The setting described here is tuned to some extent for oil exploration, however, it can be modified to deal with other activities including: mining, natural and shale gas, and other natural explorations. Another extension to our setup is to account for the option to mothball exploration and/or extraction (once extraction begins), as well as other managerial flexibilities that might arise in exploration and investment. See for example McDonald and Siegel (1985), Dixit and Pindyck (1994), Trigeorgis (1996), Tsekrekos (2010), Jaimungal and Lawryshyn (2015), and Kobari et al. (2014). We first describe how we model technical uncertainty and then describe how we model project value uncertainty. As usual, we assume a filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, \mathbb{P})$ where the filtration $\{\mathcal{F}_t\}_{t \geq 0}$ will be described in more detail at a later stage. We also assume the existence of an equivalent martingale measure, or risk-neutral measure, \mathbb{Q} and all models below are written in terms of this probability measure.

2.1. Technical Uncertainty

Let $V = (V_t)_{t \geq 0}$ denote the estimated reserve volume (level) process and ϑ be the true reserve volume. The true reserve volume ϑ is unknown to the investor, and can be viewed as a random variable when conditioned¹ on the information available to her at time t , but it will be revealed as $t \rightarrow \infty$. We assume for simplicity that the possible reserve levels, as well as their estimates, take on values from a finite set of possible reserve volumes. We model the estimated reserve level as a continuous-time (inhomogeneous) Markov chain because reserve estimates are updated as new information from exploration is obtained. Moreover, to capture the feature that the accuracy of estimates improves as more information becomes available through time, we assume that the transition rate between the volume estimate states decreases as time flows forward. In addition, we assume that $\lim_{t \rightarrow \infty} V_t = \vartheta$ almost surely to reflect the feature mentioned earlier that the true reserve level is revealed to the investor with the passage

¹For which we need to assume that $\vartheta < \infty$ almost surely.

of time.²

More specifically, the estimated reserve volume V_t is modulated by a finite state, continuous-time, inhomogeneous Markov chain Z_t taking values in $\{1, \dots, m\}$ via

$$V_t = v^{(Z_t)}, \quad (2)$$

where the constants

$$\{v^{(1)}, \dots, v^{(m)}\} \in \mathbb{R}_+^m \quad (3)$$

are the possible reserve volumes. The generator matrix of the Markov chain Z_t is denoted by \mathbf{G}_t and assumed to be of the form

$$\mathbf{G}_t = h_t \mathbf{A}, \quad (4)$$

where h_t is a deterministic, non-negative decreasing function of time, such that $h_t \xrightarrow{t \rightarrow \infty} 0$ and $\int_0^\infty h_u du < \infty$, and \mathbf{A} is a constant $m \times m$ matrix with $\sum_{j=1}^m A_{ij} = 0$ and $A_{ij} > 0$ for $i \neq j$. The states of the Markov chain correspond to various possible estimates for reserve level, thus capturing the uncertainty in those estimates.

The function h_t captures how the agent learns about the volume or quantity of the commodity in the reserve. A decreasing h implies that the transition rates are also decreasing, and hence the probability of changes in the estimated volumes decreases with time, and therefore the estimates become more accurate. Optimal policies for the irreversible investment to explore, and the subsequent value of the project based on the extraction of the commodity, naturally depend on the observed estimate of reserves – Section 4 discusses in detail the form of h_t and \mathbf{A} , and how they are calibrated to data.

2.2. Market Uncertainty

The second source of uncertainty stems from the spot price of the commodity which we denote by $S = (S_t)_{t \geq 0}$, and is modelled as the exponential of an Ornstein-Uhlenbeck (OU) process:

$$S_t = \exp\{\theta + X_t\}, \quad (5a)$$

where the OU process $X = (X_t)_{t \geq 0}$ satisfies the stochastic differential equation (SDE)

$$dX_t = -\kappa X_t dt + \sigma dW_t, \quad (5b)$$

where $W = (W_t)_{t \geq 0}$ is a standard Brownian motion (independent of Z), $\kappa > 0$ is the rate of mean-reversion, θ is the (log-)level of mean-reversion, and σ is the (log-)volatility of the

²We could in principle derive such a model by writing $V_t = \mathbb{E}[v | \mathcal{G}_t]$ where $\mathcal{G} = (\mathcal{G}_t)_{t \geq 0}$ denotes the filtration that generates our information about the true reserve. Under some specific modeling assumptions, V can be cast into a Markov chain representation. We opt not to delve into these details, as it detracts from the simplicity of the approach we are proposing, and instead model V directly.

spot price. Such models of commodity spot prices have been widely used in the literature, see for example Cartea and Figueroa (2005), Weron (2007), Cartea and Williams (2008), Kiesel et al. (2009), Coulon et al. (2013).

Now that we have specified the model for the stock of the commodity in the reserve and its market price, we need one final ingredient: the market value of the commodity in the reserve. We denote this value by the process $P = (P_t)_{t \geq 0}$ and show how to calculate it in steps.

Suppose that investment is made at time t , which is followed by extraction of the commodity $\epsilon \geq 0$ later, and extraction continues until the random (stopping) time $\tau = t + \epsilon + \Delta$. Here $\Delta > 0$ represents the amount of time required to complete the extraction process. The investor does not know how much of the commodity is in the reserve, so the time to depletion (and the extraction duration) is a random stopping time. We also note that engineering and physical limitations prevent the total amount of the commodity stored in the reserve from being extracted, and instead only $\gamma \vartheta$ is extractable, $0 < \gamma < 1$.³

The random time to depletion Δ is related to the unknown total reserve volume ϑ via the rate of extraction. In particular, we have:

$$\int_{t+\epsilon}^{t+\epsilon+\Delta} g(u) du = \gamma \vartheta, \quad (6)$$

where $g(u)$ denotes the rate of extraction at time u . We assume that once extraction begins the commodity is extracted at the rate

$$g(u) = \alpha e^{-\beta(u-(t+\epsilon))}, \quad u \in [t + \epsilon, t + \epsilon + \Delta], \quad (7)$$

where $\alpha \geq 0$, and $\beta \geq 0$. Figure 1 presents a stylized picture of the exponential extraction rate (7). Under the specific extraction rate model in (7), the time to depletion can be written as

$$\Delta = -\frac{1}{\beta} \log \left(1 - \frac{\beta}{\alpha} \gamma \vartheta \right), \quad (8)$$

which is a random variable because ϑ is only known as $t \rightarrow \infty$.

The value of the reserve when extraction begins is determined by a number of factors including: the price of the commodity, the state of the Markov chain linked to reserve uncertainty, and the random time to exhaustion of the reserve. Specifically, the discounted value of the cash-flow generated from extracting the commodity at the rate $g(u)$ and selling it at the spot price S_u is given by

$$DCF_t = \int_{t+\epsilon}^{t+\epsilon+\Delta} e^{-\rho(u-t)} (S_u - c) g(u) du, \quad (9)$$

³A good example is stored natural gas where there is always a residual that cannot be extracted from storage.

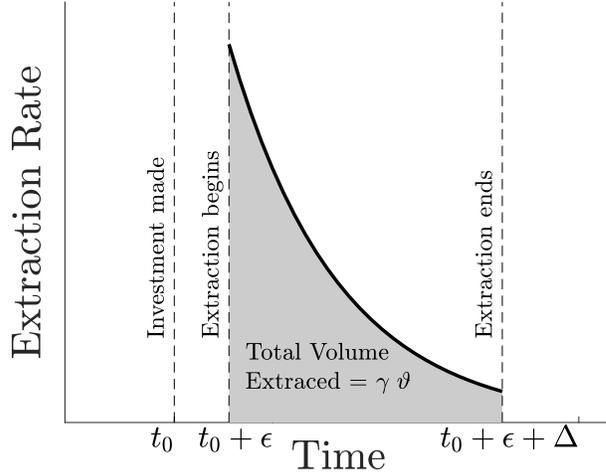


Figure 1: Once the agent invests in the reserve at time t , extraction begins a time $t + \epsilon$ and continues until γ percentage of the actual (unknown) reserve volume ϑ is extracted, which occurs at the random time $t + \epsilon + \Delta$.

where ρ is the agent's discount factor for the level of risk she bears with the project and c is a running cost that the investor incurs as long as the extraction operation lasts.

To compute the market value of the commodity in the reserve, which we denote by P_t , we calculate the expected discounted value of the cash flows attained from selling the extracted commodity. Namely, we insert in (9): the spot price of the commodity (5), the time to extraction completion given in (8), and the extraction rate (7). Finally, we take expectations of DCF_t to obtain

$$P_t = \mathbb{E}[DCF_t | \mathcal{F}_t] = \mathbb{E} \left[\int_{t+\epsilon}^{t+\epsilon+\Delta} e^{-\rho(u-t)} (F_t(u) - c) g(u) du \middle| \mathcal{F}_t \right], \quad (10)$$

where $\mathcal{F}_t = \sigma((S_u, V_u)_{u \in [0, t]})$ is the natural filtration generated by both S and V (or equivalently the Markov chain Z introduced earlier), the expectation is taken under the risk-neutral measure \mathbb{Q} and

$$\begin{aligned} F_t(u) &= \mathbb{E}[S_u | \mathcal{F}_t] \\ &= \exp \left\{ \theta + e^{-\kappa(u-t)} x + \frac{\sigma^2}{4\kappa} (1 - e^{-2\kappa(u-t)}) \right\} \end{aligned}$$

is the forward price of the underlying asset.

Thus, the expectation in (10) is over the random time to depletion Δ , which further depends on the reserve volume ϑ . To compute this expectation we require the conditional distribution of the unknown reserve level ϑ , that is we require $\mathbb{P}(\vartheta = v^{(j)} | \mathcal{F}_t)$. By our assumption that $\vartheta = \lim_{t \rightarrow \infty} V_t$ a.s., this requires determining the conditional distribution at time t of the limit of the underlying Markov chain. Specifically,

$$\mathbb{P}(\vartheta = v^{(j)} | \mathcal{F}_t) = \mathbb{P} \left(\lim_{t \rightarrow \infty} V_t = v^{(j)} \middle| \mathcal{F}_t \right) = \mathbb{P} \left(\lim_{t \rightarrow \infty} Z_t = j \middle| Z_t = i \right) = [e^{H_t \mathbf{A}}]_{ij},$$

where $H_t = \int_t^\infty h_u du$, the notation $[\cdot]_{ij}$ denotes the ij element of the matrix in the square brackets, and recall that the matrix \mathbf{A} is defined above in (4). Therefore, the final expression for the expected discounted value of the reserve is

$$P_t := p^{(Z_t)}(t, X_t) = \sum_{j=1}^m [e^{H_t} \mathbf{A}]_{Z_t, j} \int_{t+\epsilon}^{t+\epsilon - \frac{1}{\beta} \log \left(1 - \frac{\beta}{\alpha} \gamma v^{(j)} \right)} e^{-\rho(u-t)} (F_t(u) - c) g(u) du. \quad (11)$$

This expression has two sources of uncertainty, the first stems from the spot price of the commodity, through the OU process X_t , and the second from the estimate of the reserve volume, through the state of the Markov chain Z_t . With the model of extraction rate being exponentially decaying in time, see (7), it is possible to write the integral appearing in the right-hand side of equation (11) in terms of special functions, however, such a rewrite does not add clarity so we opt to keep the integral as shown above.

3. Real Option Valuation

Now that we have a model for the value of the reserve, we focus on the cost required to exploit the reserve of the commodity and the value of the flexibility to decide when to make the investment. The cost of investing in the reserve is irreversible and denoted by $I^{(k)}$, where k is the regime of the reserve volume estimate. Here we assume that the cost $I^{(k)}$ is linked to the volume estimate because extracting a large reserve will likely require a larger up-front investment than that required to extract the commodity from a small reserve. We assume that the investment cost is

$$I^{(k)} = c_0 + c_1 v^{(k)}, \quad (12)$$

where $c_0 \geq 0$ is a fixed cost, $c_1 \geq 0$, and recall that $v^{(k)}$ are the possible reserve volumes, see (3). Notice that the investment cost depends on the reserve estimate. This reflects the fact that the investor will base the size of their extraction operation on their estimate of the reserve amount: the larger they believe the reserve to be, the bigger the required operation. The running cost c ensures that the investor's running cost is still tied to the true reserve amount.

We denote the value of the option by $L_t = \ell^{(Z_t)}(t, X_t)$, where the collection of functions $\ell^{(1)}(t, x), \dots, \ell^{(m)}(t, x)$ represents the value of the real option conditional on the state $Z_t = 1, \dots, m$ (indexed by the superscript) and $X_t = x$. The agent must make a decision by time T , or they will lose the option to make the investment and exploit the reserve. Standard theory implies that the value of the option to irreversibly invest in the reserve, and begin extraction, is given by the optimal stopping problem:

$$L_t = \sup_{\tau \in \mathcal{T}} \mathbb{E} \left[e^{-\rho\tau} \max (P_\tau - I^{(Z_\tau)}, 0) \mid \mathcal{F}_t \right] \quad (13a)$$

$$= \sup_{\tau \in \mathcal{T}} \mathbb{E} \left[e^{-\rho\tau} \max (P_\tau - I^{(Z_\tau)}, 0) \mid Z_t, X_t \right]. \quad (13b)$$

Here, \mathcal{T} denotes the set of admissible stopping times, taken to be the finite collection of \mathcal{F} -stopping times restricted to $t_i = i\Delta t$, $i = 0, \dots, N$ with $t_N \leq T$. In other words, the agent is restricted to making the investment decision on days t_i . In the interim time, the agent can acquire more information to improve her volume reserve estimates.

For notational convenience we define the deflated value process

$$\bar{\ell}^{(j)}(t, x) := e^{-\rho t} \ell^{(j)}(t, x), \quad (14)$$

and observe that in between the investment dates, the deflated value processes $\bar{\ell}^{(j)}(t, x)$ for $j = 1, \dots, m$, are martingales. In addition, since in between the investment dates there is no opportunity to exercise the option, $\bar{\ell}^{(j)}(t, x)$ is the same as a European claim with payoff equal to the value at the next exercise date. Thus,

$$\bar{\ell}^{(j)}(t_i, x) = \max \left(\lim_{t \downarrow t_i} \bar{\ell}^{(j)}(t, x); e^{-\rho t_i} (p^{(j)}(t, x) - I^{(j)}) \right), \quad (15)$$

where $p^{(j)}(t, x)$ is as in (11), and recall that $j = 1, \dots, m$ represents the state of the regime.

Finally, in the interval $t \in (t_i, t_{i+1}]$ the processes $\bar{\ell}^{(j)}(t, x)$ satisfy the coupled system of PDEs

$$(\partial_t + \mathcal{L}) \bar{\ell}^{(j)}(t, x) + h_t \sum_{j=1}^m A_{jk} \bar{\ell}^{(k)}(t, x) = 0, \quad t \in (t_i, t_{i+1}], \quad (16)$$

where $\mathcal{L} = -\kappa x \partial_x + \frac{1}{2} \sigma^2 \partial_{xx}$ is the infinitesimal generator of the process X_t .

The maximization in (15) represents the agent's option to hold on to the investment option at time t_i or to invest immediately. If the second argument attains the maximum, then the agent exercises her option to invest in the reserve, at a cost of $I^{(j)}$, and receives the expected discounted value of the cash-flow $p^{(j)}(t, x)$, which results from extracting and selling the commodity on the spot market. This investment decision is tied to the reserve volume estimate through the regime j . Different regimes j will result in different exercise policies and we explore this relationship in the next section.

Motivated by the work of Jaimungal and Surkov (2011), who study options on multiple commodities driven by Lévy processes, we solve the system of PDEs (16) recursively by employing the Fourier transform of $\bar{\ell}^{(j)}(t, x)$ with respect to x , which we denote by $\tilde{\ell}^{(j)}(t, \omega)$. Specifically, we write

$$\tilde{\ell}^{(j)}(t, \omega) = \int_{-\infty}^{\infty} e^{-i\omega x} \bar{\ell}^{(j)}(t, x) dx, \quad \text{and} \quad \bar{\ell}^{(j)}(t, x) = \int_{-\infty}^{\infty} e^{i\omega x} \tilde{\ell}^{(j)}(t, \omega) \frac{d\omega}{2\pi}, \quad (17)$$

where $\iota = \sqrt{-1}$. Applying the Fourier transform to (16), we obtain a new PDE, without the parabolic term, which depends on the state variable ω rather than the state variable x , i.e.:

$$[\partial_t + (\kappa - \frac{1}{2} \sigma^2 \omega^2) + \kappa \omega \partial_\omega] \tilde{\ell}^{(j)}(t, \omega) + h_t \sum_{j=1}^m A_{jk} \tilde{\ell}^{(k)}(t, \omega) = 0. \quad (18)$$

Within the interval $(t_k, t_{k+1}]$, we introduce a moving coordinate system and write $\hat{\ell}^{(j)}(t, \omega) = \tilde{\ell}^{(j)}(t, e^{-\kappa(t_{k+1}-t)}\omega)$, which removes the derivative in ω and we find that the functions $\hat{\ell}^{(j)}$ satisfy the coupled linear system of ODEs

$$\partial_t \hat{\ell}^{(j)}(t, \omega) + \left(\kappa - \frac{1}{2} \sigma^2 \omega^2 e^{-2\kappa(t_{k+1}-t)} \right) \hat{\ell}^{(j)}(t, \omega) + h_t \sum_{j=1}^m A_{jk} \hat{\ell}^{(k)}(t, \omega) = 0. \quad (19)$$

By writing $\mathbf{A} = \mathbf{U} \mathbf{D} \mathbf{U}^{-1}$ where \mathbf{U} is the matrix of eigenvectors of \mathbf{A} , and \mathbf{D} the diagonal matrix of eigenvalues of \mathbf{A} , the above coupled system of ODEs can be recast as independent ODEs, which in vector form reads

$$\partial_t \left(\mathbf{U}^{-1} \hat{\boldsymbol{\ell}}(t, \omega) \right) + \left(\psi(\omega e^{-\kappa(t_{k+1}-t)}) \mathbb{I} + h_t \mathbf{D} \right) \mathbf{U}^{-1} \hat{\boldsymbol{\ell}}(t, \omega) = \mathbf{0}, \quad (20)$$

where $\hat{\boldsymbol{\ell}}(t, \omega) = (\hat{\ell}^{(1)}(t, \omega), \dots, \hat{\ell}^{(n)}(t, \omega))'$, $\psi(\omega) = \kappa - \frac{1}{2} \sigma^2 \omega^2$ and \mathbb{I} is the $n \times n$ identity matrix. These uncoupled ODEs have solution

$$\mathbf{U}^{-1} \hat{\boldsymbol{\ell}}(t_k^+, \omega) = \exp \left\{ \int_{t_k}^{t_{k+1}} \psi(\omega e^{-\kappa(t_{k+1}-s)}) ds \mathbb{I} + \int_{t_k}^{t_{k+1}} h_s ds \mathbf{D} \right\} \mathbf{U}^{-1} \hat{\boldsymbol{\ell}}(t_{k+1}, \omega). \quad (21)$$

where $\hat{\boldsymbol{\ell}}(t_{k+}, \omega) = \lim_{t \downarrow t_k} \hat{\boldsymbol{\ell}}(t, \omega)$.

Next, we left-multiply by \mathbf{U} to obtain

$$\hat{\boldsymbol{\ell}}(t_k^+, \omega) = \exp \left\{ \int_{t_k}^{t_{k+1}} \psi(\omega e^{-\kappa(t_{k+1}-s)}) ds \right\} \exp \left\{ \int_{t_k}^{t_{k+1}} h_s ds \mathbf{A} \right\} \hat{\boldsymbol{\ell}}(t_{k+1}, \omega), \quad (22)$$

and the Fourier transform of the deflated value of the option to irreversibly invest is

$$\tilde{\boldsymbol{\ell}}(t_k^+, \omega) = \exp \left\{ \int_0^{t_{k+1}-t_k} \psi(\omega e^{\kappa s}) ds \right\} \exp \left\{ \int_{t_k}^{t_{k+1}} h_s ds \mathbf{A} \right\} \tilde{\boldsymbol{\ell}}(t_{k+1}, \omega e^{\kappa(t_{k+1}-t_k)}). \quad (23)$$

This result has a few interesting features. The first is that the role of mean-reversion decouples from the Markov chain driving the volume estimates. The second is that the value at time t_k^+ at frequency ω depends on the value at time t_{k+1} at frequency $\omega e^{\kappa(t_{k+1}-t_k)}$. This requires an extrapolation in the frequency space as the algorithm to calculate the option value steps backward in time. When we discretize the state space, such extrapolations could lead to inaccurate results since the edges of the state space are the most important contributions to the extrapolated values. Instead, we make use of the inverse relationship between frequencies and real space in Fourier transforms

$$\int_{-\infty}^{\infty} e^{i\omega x} g(x/a) dx = \int_{-\infty}^{\infty} e^{i(a\omega)x} g(x) \frac{dx}{a} = \frac{1}{a} \tilde{g}(a\omega),$$

to write

$$\tilde{\boldsymbol{\ell}}(t_k^+, \omega) = \exp \left\{ \int_0^{t_{k+1}-t_k} \psi(\omega e^{\kappa s}) ds \right\} \exp \left\{ \int_{t_k}^{t_{k+1}} h_s ds \mathbf{A} \right\} \tilde{\boldsymbol{\ell}}(t_{k+1}, \omega),$$

where $\check{\ell}(t_{k+1}, x) = \ell(t_{k+1}, x e^{-\kappa(t_{k+1}-t_k)})$ and $\check{\check{\ell}}$ denotes the Fourier transform of $\check{\ell}$. Thus the value of the right-limit of the real option to invest at t_k^+ is determined in terms of interpolation in x (rather than extrapolation in ω). In Figure 2 we summarize the approach for valuing the real option to irreversibly invest in the reserve.

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1. **Set the real and frequency space grids**
 $x = [-\bar{x} : \Delta x : \bar{x}]$, $\check{x} = e^{-\kappa \Delta t} x$ and $\omega = [0 : \Delta \omega : \bar{\omega}]$.
 2. **Place terminal conditions:** $\ell(t_n, x) = e^{-\rho t_n} (\mathbf{P}(t_n, x) - \mathbf{I})_+$.
 3. **Set $k = n$.**
 4. **Step backwards from t_{k+1} to t_k :**
 - (a) $\check{\ell}_{t_{k+1}} = \text{interp}(x, \ell_{t_{k+1}}, \check{x})$
 - (b) $\check{\check{\ell}}_{t_{k+1}}(\omega) = \mathbf{F}[\check{\ell}_{t_{k+1}}(x)]$
 - (c) $\check{\ell}_{t_k^+}(x) = \mathbf{F}^{-1} \left[e^{\int_0^{t_{k+1}-t_k} \psi(\omega e^{\kappa s}) ds} e^{\int_{t_k}^{t_{k+1}} h_s ds} \mathbf{A} \check{\check{\ell}}_{t_{k+1}}(\omega) \right]$
 - (d) $\check{\ell}_{t_k} = \max \left(\check{\ell}_{t_k^+}(x); e^{-\rho t_k} (\mathbf{P}(t_k, x) - \mathbf{I})_+ \right)$
 5. **Set $k \rightarrow k - 1$, if $k \geq 0$ go to step 4.**
-
-

Figure 2: Algorithm for computing the value of the option to irreversibly invest in the reserve.

4. Calibration and learning

Armed with the model in Section 2, and the valuation procedure developed in Section 3, we discuss in detail the calibration procedure for the Markov chain parameters and the investor's learning function h_t given by (4). The general idea is to use the investor's prior information regarding the estimate to define the possible reserve estimates, represented by the states of the Markov chain, as well as the transition rates for the base generator matrix \mathbf{A} . The next step is to calibrate the learning function using information about how much the reserve estimate variance can be reduced by some future date.

4.1. Calibration of Markov chain parameters

At time $t = 0$ the agent has an estimate of the true reserve volume, denoted by μ , and the volatility of the estimate, denoted by σ_0 . Thus

$$\mu = \mathbb{E}[\vartheta | \mathcal{F}_0] \quad \text{and} \quad \sigma_0^2 = \mathbb{V}[\vartheta | \mathcal{F}_0]. \quad (24)$$

The first step in the calibration procedure is to select the states of reserve volume conditional on the Markov chain state, i.e. to select $v^{(1)}, \dots, v^{(m)}$. Since the $t = 0$ estimate of the reserve volume represents an unbiased estimator of the reserves, the Markov chain should be

symmetric around the initial estimate of the reserve volume. To ensure this symmetry, we assume that (i) the cardinality of the states of the Markov chain Z_t is odd, i.e., $m = 2L + 1$ for some positive integer L ; (ii) $v^{(L+1)} = \mu$ where μ is the initial estimate of the reserve volume, (iii) $v^{(k)}$ is increasing in k and (iv)

$$v^{(L+1+i)} - \mu = \mu - v^{(L+1-i)}, \quad \forall i = 1, \dots, L. \quad (25)$$

We further assume that the agent's estimate of the volume is normally distributed (this assumption can be modified to any distribution the agent considers to represent her prior knowledge):

$$\vartheta | \mathcal{F}_0 \sim \mathcal{N}(\mu, \sigma_0^2), \quad (26)$$

Therefore, we choose $v^{(k)}$ to be equally spaced over n standard deviations of the normal random variable support, i.e., we select

$$v^{(k)} = \mu - n\sigma_0 + (k-1) \frac{2n\sigma_0}{m-1}, \quad \forall k = 1, \dots, m \quad (27)$$

Placing symmetry on the states of the reserve volume estimator is not sufficient to ensure symmetry in its distribution. We further require the symmetry in the base generator rate matrix \mathbf{A} , and assume that

$$\mathbf{A}_{1,1}^\lambda = -\lambda_1, \quad \mathbf{A}_{1,2}^\lambda = \lambda_1, \quad (28a)$$

$$\mathbf{A}_{i,i-1}^\lambda = \lambda_i, \quad \mathbf{A}_{i,i}^\lambda = -2\lambda_i, \quad \mathbf{A}_{i,i+1}^\lambda = \lambda_i, \quad i = 2, \dots, L, \quad (28b)$$

$$\mathbf{A}_{L+1,L}^\lambda = \lambda_{L+1}, \quad \mathbf{A}_{L+1,L+1}^\lambda = -2\lambda_{L+1}, \quad \mathbf{A}_{L+1,L+2}^\lambda = \lambda_{L+1}, \quad (28c)$$

$$\mathbf{A}_{m-i,m-i-1}^\lambda = \lambda_i, \quad \mathbf{A}_{m-i,m-i}^\lambda = -2\lambda_i, \quad \mathbf{A}_{m-i,m-i+1}^\lambda = \lambda_i, \quad i = 1, \dots, L-1, \quad (28d)$$

$$\mathbf{A}_{m,m-1}^\lambda = \lambda_1, \quad \mathbf{A}_{m,m}^\lambda = -\lambda_1. \quad (28e)$$

for some set of $\boldsymbol{\lambda} = \{\lambda_1, \lambda_2, \dots, \lambda_{L+1}\}$, where $\lambda_1, \lambda_2, \dots, \lambda_{L+1} > 0$. Here $\lambda_1, \{\lambda_2, \dots, \lambda_L\}$ and λ_{L+1} determine the transition rates out of the edge states, interior states and the midstate, respectively. The form of \mathbf{A}^λ ensures transitions only occur between neighboring states and ensures symmetry in the transition rates of states that are across the mean estimate. The parameters $\boldsymbol{\lambda}$ are calibrated so the invariant distribution of ϑ without learning coincides with a discrete approximation of a normal random variable with mean μ and variance σ_0^2 . This ensures that the Markov chain generates an invariant distribution equal to a discrete approximation of the original estimate of the reserve volume distribution. Formally, let $\mathbf{P}^\lambda = e^{\mathbf{A}^\lambda}$ denote the transition probability after one unit of time, and let $\boldsymbol{\pi}^\lambda$ denote the invariant distribution of \mathbf{P} , i.e., $\boldsymbol{\pi}^\lambda$ solves the eigenproblem $\mathbf{P} \boldsymbol{\pi}^\lambda = \boldsymbol{\pi}^\lambda$. Then, we choose $\boldsymbol{\lambda}$ such that

$$\boldsymbol{\pi}_1^\lambda = \Phi_{\mu,\sigma_0} \left(\frac{1}{2} (v^{(1)} + v^{(2)}) \right) - \Phi_{\mu,\sigma_0} \left(\frac{1}{2} (v^{(1)} + [v^{(1)} - (v^{(2)} - v^{(1)})]) \right), \quad (29a)$$

$$\boldsymbol{\pi}_2^\lambda = \Phi_{\mu,\sigma_0} \left(\frac{1}{2} (v^{(i+1)} + v^{(i)}) \right) - \Phi_{\mu,\sigma_0} \left(\frac{1}{2} (v^{(i)} + v^{(i-1)}) \right), \quad i = 2, \dots, 2L, \quad (29b)$$

$$\boldsymbol{\pi}_m^\lambda = \Phi_{\mu,\sigma_0} \left(\frac{1}{2} (v^{(m)} + [v^{(m)} + (v^{(m)} - v^{(m-1)})]) \right) - \Phi_{\mu,\sigma_0} \left(\frac{1}{2} (v^{(m)} + v^{(m-1)}) \right), \quad (29c)$$

where $\Phi_{\mu,\sigma_0}(\cdot)$ denotes the normal cumulative density of a normal with mean μ and variance σ_0^2 . Note that Φ_{μ,σ_0} is evaluated at the midpoint between possible reserve amounts and that we extrapolate linearly to obtain the equations for the edge states.

4.2. Calibration of the learning function

As time passes, the agent gathers more and better quality information about the volumes of the commodity in the reserve. Thus, the variance of the estimated volume in the reserve is expected to decrease from σ_0^2 to $\sigma_{T'}^2 < \sigma_0^2$ by some fixed time $T' < T$. Specifically⁴

$$\sigma_{T'}^2 = \mathbb{V}[\vartheta | \mathcal{F}_{T'}]. \quad (30)$$

This parameter, along with the starting reserve estimate variance, σ_0^2 , are the main determinants of the learning function. For parsimony, we assume that the agent's learning function is of the form

$$h_t = a e^{-bt} \quad \text{for some } a, b > 0,$$

where the parameter a represents the initial transition rates, i.e. $h_0 = a$, between the states of the Markov chain, and hence reflects the uncertainty in the initial estimates of reserves. The learning parameter b represents the rate at which the agent learns – the larger (resp. smaller) is b the quicker is the learning process because large (resp. small) values of b make the transition rates decay faster (slower) through time and therefore reserve estimates become stable quickly (resp. slowly). Recall that the learning rate function plays a key role in the generator matrix of the Markov chain, see (4), in that it captures how the agent learns how much volume of the commodity is in the reserve.

The parameters in the learning rate function h are calibrated to obey the constraints (24) and (30). Due to the symmetry in the base transition rates \mathbf{A} , and the symmetry in the reserve volume states $v^{(k)}$, we automatically satisfy the mean constraints

$$\mathbb{E}[\vartheta | V_0 = \mu] = \mu, \quad \text{and} \quad \mathbb{E}[\vartheta | V_{T'} = \mu] = \mu. \quad (31)$$

To satisfy the variance constraints we require the transition probabilities of the Markov chain from an arbitrary state at time t to its infinite horizon state, which we denote $p_{t,ij} := \mathbb{P}\left(\lim_{t \rightarrow \infty} Z_t = j \mid Z_t = i\right)$, to be

$$p_{t,ij} = [\exp\{(\int_t^\infty h_u du) \mathbf{A}\}]_{ij} = [\exp\{\frac{a}{b} e^{-bt} \mathbf{A}\}]_{ij}. \quad (32)$$

Note that the right-hand side of the equation above is a matrix exponential and, as before, the notation $[\cdot]_{ij}$ denotes the ij element of the matrix in the square brackets. Now we must solve the two coupled system of non-linear equations for the parameters a and b :

$$\sigma_0^2 = \mathbb{V}[\vartheta | V_0 = \mu] = \sum_{k=1}^{2L+1} v^{(k)} (p_{0,Lk} - \mu)^2, \quad (33a)$$

$$\sigma_{T'}^2 = \mathbb{V}[\vartheta | V_{T'} = \mu] = \sum_{k=1}^{2L+1} v^{(k)} (p_{T',Lk} - \mu)^2, \quad (33b)$$

⁴In principle, we could develop a model that can calibrate to a sequence of times and variances, however, the one step reduction is enough to illustrate the essential ideas in this reduction.

where $\mathbb{V}[\cdot|\cdot]$ is the variance operator of the first argument conditioned on the event in the second argument.

After which, all technical uncertainty model parameters are calibrated to the distributional properties of the initial reserve volume estimates and the reduction in variance as a result of learning.

The value of the irreversible option to invest in the reserve with learning can now be valued using the approach in Section 3, a summary of which is presented in the algorithm shown in Figure 2. The value of exploration, which improves the variance of the estimators of the reserve volume, can be assessed by considering the option value when there is no learning and comparing it to the option value without learning.

5. Numerical Results

In this section we investigate the optimal exercise policies of the agent and assess the value of learning. Throughout we use the following parameters and modeling choices:

- **Reserve volume.** Initial reserve estimate: $\mu = 10^9$, initial reserve estimate variance: $\sigma_0^2 = 3 \times 10^8$.
- **Investment costs.** Fixed cost parameter: $c_0 = 10^8$, variable cost parameter: $c_1 = 3 \times 10^6$. This implies an investment cost of 1.12×10^8 when the reserve estimate is lowest and 1.48×10^8 when the reserve estimate is highest.
- **Expiry of option.** $T = 5$ years which consists of 255 weeks.
- **Other model parameters:**
 - Underlying resource model parameters: $\kappa = 0.5$, $\theta = \log(100)$, $\sigma_X = 0.5$.
 - Discount rate: $\rho = 0.05$.
 - Extraction rate parameters: $\alpha = 1$, $\beta = 0.05$, $\gamma = 0.9$, $\epsilon = 2$.
 - Markov chain parameters: 31 states.

Furthermore, we will consider the case of slow learning and fast learning which we model by changing the reduction in reserve estimate variance ($\sigma_{T'}^2 = 2.5 \times 10^8$ versus $\sigma_{T'}^2 = 10^8$) with $T' = 2$ years. We also will consider the case with and without running costs ($c = 20$ and $c = 0$, respectively). Finally, we compare these to the case where this is no learning by setting $a = 1$ and $b = 0$.

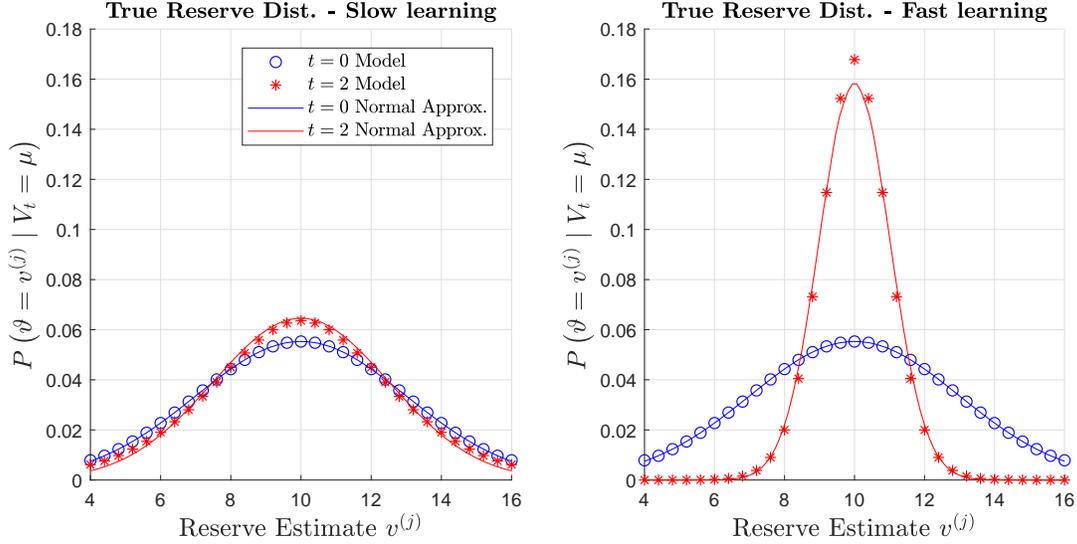


Figure 3: Model-implied distribution of true reserve amount at $t = 0$ and $t = 2$ (variance reduction timeframe) conditional on being at the initial estimate $\mu = v^{(L+1)}$ in the case of slow learning (left panel) and fast learning (right panel). Lines correspond to normal approximations for the invariant distribution with parameters (μ, σ_0^2) and (μ, σ_T^2) , respectively.

Figure 3 shows the effect of learning on the distribution of the true reserve amount. We find that in both the slow and fast learning cases, the distribution (conditional on being at the initial reserve estimate) is more peaked around the mid-state. This reflects the fact that the investor has learned more about the reserve amount and, given that they are in the mid-state at $t = 2$ (the timeframe given for calibrated variance reduction), they are now more inclined to believe that μ is the true reserve amount. This effect is slight in the slow learning case and more pronounced with fast learning as the investor is more confident having learned more about the reserve in the same amount of time. Note that the model-implied probabilities match the normal approximation only at $t = 0$ since this was the only constraint imposed in the calibration procedure.

Figure 4 shows the optimal exercise boundary for an agent who learns at different rates and for different volume estimates (i.e. different states of the Markov chain). For simplicity, we only display a select number of states near the mid-state as these represent the most relevant volume estimates for the investor. The y -axis of the figure shows the spot price of the commodity at which the investor would exercise the option, and the x -axis is the time elapsed measured in years. The figure shows that as the agent's volume estimate increases, the exercise boundary shifts down because a larger reserve requires a lower commodity spot price to justify the investment.

We observe that the inclusion of learning, both fast and slow, has a profound effect on the shape of the exercise boundary. In the no-learning case, this boundary is non-increasing with time whereas the cases of slow and fast learning lead to exercise boundaries with non-

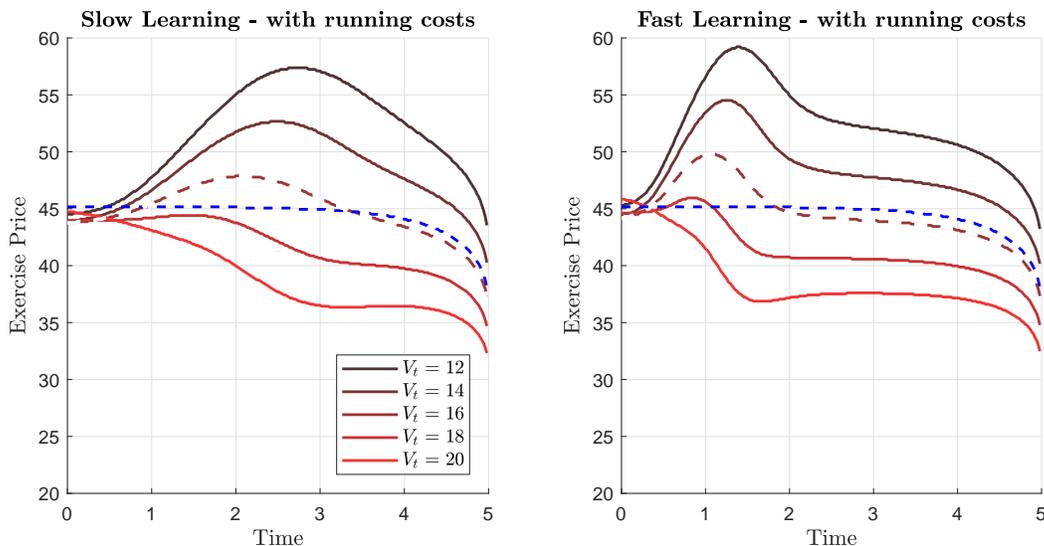


Figure 4: Exercise boundary for different reserve estimates states when the agent’s learning rate is low (left panel) vs. high (right panel) when they incur running costs. Brighter lines correspond to higher reserve estimates, the dashed red line corresponds to the middle state (initial reserve estimate) and the blue line is the exercise boundary when there is no learning.

trivial shapes that include increases and decreases at different rates, with behavior varying depending on the investor’s prevailing reserve estimate. The explanation for the general shape these curve takes is as follows: when the investor is in a low state (i.e. has a low reserve estimate) the boundary is increasing to allow the learning process to potentially drive the estimate upward leading to a higher project value in the event that the reserve estimate increases. Eventually, the investor believes that the learning process has provided enough information to be confident that whatever state they currently occupy is in fact the true reserve amount. At this point the exercise boundary goes back to the typical decreasing pattern. The time at which this “inflection point” occurs depends on the rate of learning: when learning is fast, this turnaround comes sooner.

Figure 5 shows the exercise boundaries, for different volume states, when the agent does not incur running costs. Observe that the exercise boundaries in both the fast and slow learning case have the same general shape as the boundaries in Figure 4. The effect of adding running costs is an upward parallel shift of the exercise boundaries, as the commodity spot price must be higher to justify the investment after accounting of running costs.

Figure 6 compares the value of the option at different points in time for different learning rates, assuming that the investor’s estimate is equal to the initial estimate. We compare this to the case of no learning, which is very insensitive to time-to-maturity relative to the learning case.⁵ We find that the value of the option to wait-and-learn is high at the beginning and

⁵Note that since the value of the option changes very slightly with time-to-maturity in the no-learning

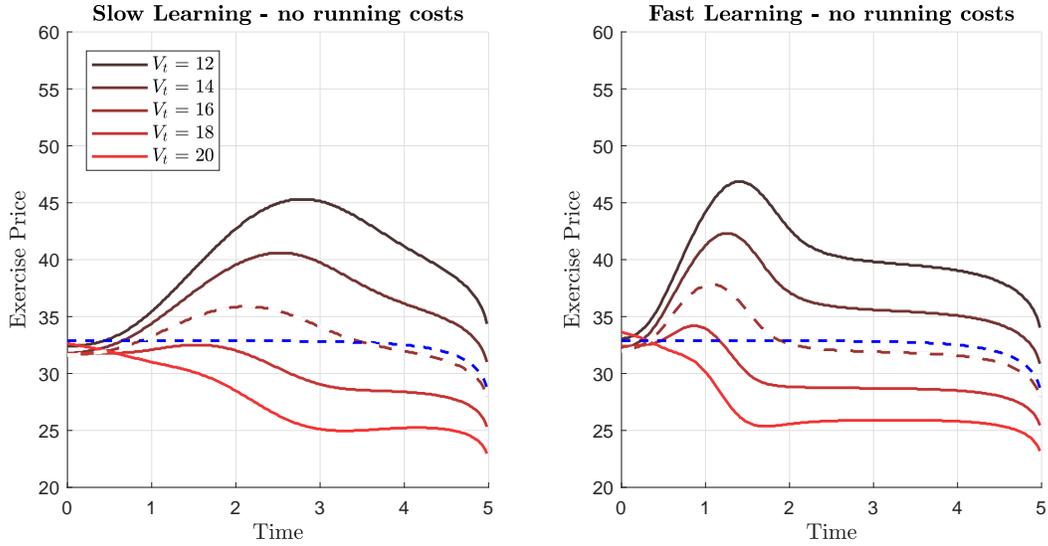


Figure 5: Exercise boundary for different reserve estimates states when the agent's learning rate is low (left panel) vs. high (right panel) when they do not incur running costs. Brighter lines correspond to higher reserve estimates, the dashed red line corresponds to the middle state (initial reserve estimate) and the blue line is the exercise boundary when there is no learning.

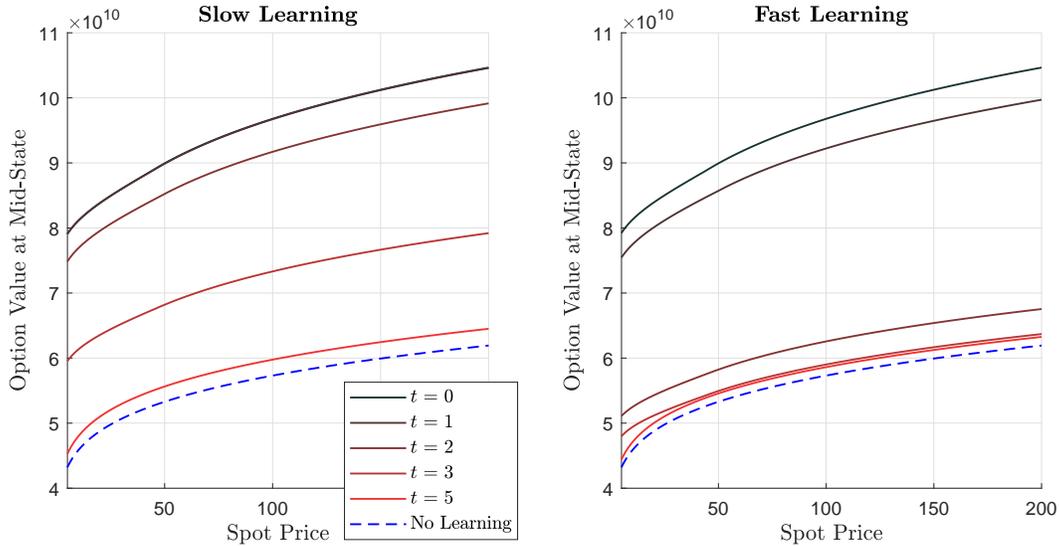


Figure 6: Option value as a function of spot price through time assuming the reserve estimate is equal to the mid-state (initial estimate), $V_t = \mu$, with slow learning (left panel) vs. fast learning (right panel). Dashed lines correspond to option value at maturity when the investor does not learn.

gradually decreases as expiry of the option approaches because the agent has little time left to learn. As expected, this decline in value is accelerated in the fast learning case as the investor becomes more confident about the reserve amount at an earlier point in time. Note that the

case, we plot the no-learning option value curve only at $t = 0$ in Figure 6.

effect of the passage of time on the option value is different in other states.

6. Conclusions

In this paper we show how to incorporate technical uncertainty into the decision to invest in a commodity reserve. This uncertainty stems from not knowing the volume of the commodity stored in the reserve, and compounds with the uncertainty of the value of the reserve because future spot prices are unknown.

The agent has the option to wait-and-see before making the irreversible investment to exploit the commodity reserve. In our model, as time goes by, the agent learns about the volume of the commodity stored in the reserve, so the option to delay investment is valuable because it allows the agent to learn and to wait for the optimal market conditions (i.e. spot price of the commodity) before sinking the investment.

We adopt a continuous-time Markov chain to model the reserve volume and the technical uncertainty. In our model the agent learns about the volume in the reserve as time goes by and the accuracy of the estimates is also improved with time. We show how to calculate the value of the option to delay investment and discuss the agent's optimal investment threshold.

We show how the exercise boundary depends on the agent's estimate of the volume (which depends on the Markov chain state) and how this boundary depends on the rate at which she refines her estimates of the reserve. For example, we show that when the option to invest is far away from expiry, and the volume estimate is low, the value attached to waiting and gathering more information is higher for the agent who can quickly learn about the volume of the reserves than for an agent who learns at a very low rate.

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