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Dynamic margin optimization

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ABSTRACT

In response to the Global Financial Crisis of 2007–2009, by now, most of the financial transactions must be cleared through central counterparties operating a dynamic margin setting mechanism. High margin calls can reduce counterparty risk in a turbulent market, but at the same time, increase liquidity risk and escalate systemic risk. In this paper, we construct a theoretical model to address this challenge, deriving an optimal margin setting policy framed as a stochastic control problem. Our analysis reveals that an adaptive, countercyclical approach is superior to a purely risk-sensitive strategy, primarily by minimizing the expected loss for the clearing institution.

1. Introduction

The 2007–2009 financial crisis underscored the critical role of counterparty risk in financial markets. In response, regulatory frameworks have increasingly mandated the central clearing of over-the-counter (OTC) transactions, pushing the share of centrally cleared OTC transactions to 75 % by 2020 (Hull, 2023). Central clearinghouses, or central counterparties (CCPs), mitigate counterparty risk by acting as intermediaries between trading parties. CCPs employ a multi-tiered risk management system, with the margin account serving as the first line of defense against defaults (Friesz and Váradi, 2023; Ghamami et al., 2023).

The regulatory response has not only focused on central clearing but also on enhancing CCPs' risk management practices by incorporating countercyclical techniques to minimize systemic risks (EMIR, 2012). The implementation of such countercyclical measures, including margin algorithms and capital buffers, has been discussed extensively from macroeconomic perspective (Brumm et al., 2015; Glasserman and Wu, 2018; Berndsen, 2021). However, it is less explored in the literature how this countercyclical margin setting affects the clearing institutions' operation from microprudential point of view. Berlinger et al. (2019b) showed analytically in a one-period model that the optimal margin level depends not only on short-term volatility expectations, but also the funding (il)liquidity of the market, suggesting that a countercyclical strategy can be optimal at a central counterparty level as well.

This paper contributes to the existing literature by deriving the optimal margin setting strategy from the perspective of the clearing institution in a multi-period model. We model the expected gap loss of a CCP caused by insufficient margin in the event of counterparty default. The simulation results show that the optimal margin level depends on the nature of the price shocks. In particular, CCPs should avoid overreactions to temporary volatility spikes. Countercyclical margin setting is preferable in the case of periodic volatility turbulences as well. The results are based on the knowledge of future volatility scenarios, and therefore, CCPs are encouraged to make more efforts to forecast volatility using all available information, including expert knowledge.

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2. Literature review

Managing counterparty risk in decentralized (Csóka and Herings, 2018) and centralized networks and the role of central counterparties gained importance following the financial crisis of 2007–2009. Brunnermeier and Pedersen (2009) highlighted the destabilizing effects of margins during periods of market stress, noting the potential for a feedback loop between market liquidity and funding liquidity. Danielsson et al. (2001, 2013) discussed the systemic risks associated with endogenous market dynamics, emphasizing the need for regulatory frameworks that mitigate procyclical behavior. This has led to increased scrutiny of CCPs' risk management practices, particularly the adequacy of their prefunded financial resources, often referred to as the "loss waterfall" (Berndsen, 2021). The initial and variable margins that CCPs require from clearing members constitute the first line of defense and are critical in mitigating counterparty risk (Shanker and Balakrishnan, 2005; Friesz and Váradi, 2023).

Several authors discussed optimal margin algorithms (Figlewski, 1984; Brennan, 1986; Hong and Lee, 2022), the efficiency of margin setting (Fenn and Kupiec, 1993) and the impact of portfolio-based margining (Szabó and Váradi, 2022) by empirical analysis or simulation techniques.

Higher margins reduce the clearing institution's counterparty risk, but also increases the trading costs of the market participants, which makes the market or the CCP itself less attractive (Longin, 1999; Pirrong, 2011). This is particularly important in emerging markets that are the first to be abandoned by investors in financial turmoil and flight to quality. Increased margin requirements may place an extra burden on market participants in a stress situation, which may lead to higher default rates in the execution of margin calls (Chande et al., 2010; Glasserman and Wu, 2018; Berlinger et al., 2019a, 2019b) and thus change the incentives for market participants to enter into central clearing voluntarily (Bellia et al., 2024). To address the procyclicality of CCPs' risk management, regulators require the use of countercyclical tools in margin setting like erodible margin buffers that are consumable under stress, margin floors, and outright margin relief (Berndsen, 2021; EMIR, 2012).

Murphy et al. (2014, 2016, 2021) argued for a cost-benefit approach to margin setting, suggesting that regulators need to carefully weigh the benefits of reducing procyclicality against the potential drawbacks of higher margin requirements in calm markets. Empirical studies offer mixed evidence on the effectiveness of countercyclical margin policies. Abruzzo and Park (2016) found that the Chicago Mercantile Exchange's margin policies were procyclical, whereas Lewandowska and Glaser (2017) observed a low correlation between market stress and margin requirements in European markets, likely due to the high collateral levels maintained by CCPs.

The countercyclical margin used by central counterparties is similar to the countercyclical capital buffers (CCyBs) for banks, designed to accumulate capital during good economic times and to utilize it during crises to prevent the collapse of their lending activity (Auer et al., 2022; Leitner et al., 2023). However, there are key differences. CCyBs are set uniformly by sovereign regulators and adjusted less than once a year based on the business cycle, a latent variable that is challenging to measure. In contrast, countercyclical margins are determined by central counterparties (CCPs) daily, tailored to each clearing member's specific portfolio, and respond to directly observable price movements. Therefore, countercyclical risk management tools and their optimal use can vary significantly depending on the area of application and the regulatory objective.

In this paper, we build on these insights by modeling the margin-setting process as a dynamic problem. Our approach relies on the credit risk model of Merton (1974) and the Credit Portfolio View developed by McKinsey and described in Crouhy et al. (2000), extending the analysis to a multi-period framework. In our model, the optimal margin minimizes the expected counterparty loss and takes into account the effects of margin requirements on the ability-to-pay and the behavior of the clearing members as well.

3. The model

We model the operation of a central counterparty, clearing a security on a futures market. Clearing members have to settle their losses and place an adequate level of initial margin defined by the CCP daily. If a clearing member fails to meet its obligation, the central counterparty closes the position immediately and settles the profit/loss on the member's account.

3.1. Security dynamics

We assume that the futures settlement price in time t (F_t) is given exogenously, following a random walk with time-dependent volatility. The ΔF_t increments are scaled independent random variables, with zero mean and with standard deviations σ_t, i.e., $\Delta F_t = \sigma_t \varepsilon_t$, with ε_t being independent, identically distributed (IID) random variables. We assume that a future volatility scenario is given, therefore, we treat the time evolution of σ_t as deterministic.

3.2. Account dynamics

The accounts of clients with both long and short positions have been filled up to the margin M_{t-1}, set in the previous period. As the futures price changes, the long and short accounts are reset as

$$A_t^{long} = M_{t-1} + \Delta F_t \tag{1}$$

$$A_t^{short} = M_{t-1} - \Delta F_t \tag{2}$$

We assume that out of the long and short positions, only the account that suffers a loss can generate gap loss for the clearing house in the given period. We therefore concentrate on the dynamics of the loser account A_t:

$$A_t = M_{t-1} - |\Delta F_t| \tag{3}$$

3.3. Probability of non-payment

After observing ΔF_t and A_t, the central counterparty sets the new margin M_t and expects the client to fill up his account to this new margin. Still monitoring the loser account, the amount of the margin call is calculated as

$$margin\ call = M_t - A_t = |\Delta F_t| + M_t - M_{t-1} \tag{4}$$

We can see that the margin call is influenced by a combination of two terms: by the (unfavorable) shift in the security price, and/or by the (possibly) increasing margin requirement. The margin call may be negative, in this case even the loser account ends up above the new margin and it will be set to the new margin by taking out cash from the account. There is no gap risk in this case. If the margin call is positive, then the loser account must be filled up, and in this case the client may decide to forfeit payment. We model the probability of non-payment as an increasing function of the margin call. One possible choice is to set p_t to zero if the "margin call" is negative, and for positive margin calls we use an exponential expression:

$$p_t = 1 - e^{-\lambda(M_t - A_t)^+} \tag{5}$$

Here, $(x)^+ = \max(0, x)$ is the positive part function. The λ parameter captures the sensitivity of the non-payment probability on the amount of the margin call. In practice, the p_t probabilities are quite low (Grothe et al., 2021), so in this paper, we will use a linearized specification:

$$p_t = \lambda(M_t - A_t)^+ \tag{6}$$

3.4. Expected gap loss given non-payment

When a client declares non-payment, his account is liquidated, and the CCP finds a new client who enters the liquidated side at the futures price in the next period. A gap loss for the CCP occurs if the forfeited account ends up in the negative, i.e., if $A_t + \Delta F_{t+1}$ becomes negative.

Assuming a symmetric distribution of ε, the expected gap loss given non-payment reads

$$L_t = E\left[(A_t + \Delta F_{t+1})^-\right] = E\left[(A_t + \sigma_{t+1}\varepsilon_{t+1})^-\right] \tag{7}$$

Here, $(x)^- = -\min(0, x)$ is the negative part function (note that it is non-negative valued). L_t is a deterministic function of A_t and σ_{t+1}, and it is first degree homogeneous in its variables. Indeed, we will write it in the form

$$L_t = \sigma_{t+1}E\left[\left(\frac{A_t}{\sigma_{t+1}} + \varepsilon_{t+1}\right)^-\right] = \sigma_{t+1} * l\left(\frac{A_t}{\sigma_{t+1}}\right) \tag{8}$$

with $l(x) = E[(x + \varepsilon)^-]$. The $l(x)$ function can be calculated for a given distribution of ε and we assume that it is strictly monotone decreasing, continuous, and differentiable.

3.5. Expected gap loss

Combining our results from the previous subsections (6) and (8), we obtain the expected gap loss for period t as

$$EL_t = p_t L_t = \lambda(M_t - A_t)^+ * \sigma_{t+1} * l\left(\frac{A_t}{\sigma_{t+1}}\right) \tag{9}$$

To analyze the margin's impact on the expected gap loss, we substitute the account dynamics $A_t = M_{t-1} - |\Delta F_t|$, see Eq. (3), to obtain

$$EL_t = \lambda(M_t - M_{t-1} + |\Delta F_t|)^+ * \sigma_{t+1} * l\left(\frac{M_{t-1} - |\Delta F_t|}{\sigma_{t+1}}\right) \tag{10}$$

The first factor is the probability of non-payment, it becomes large if we raise the margin too rapidly. The second factor is the expected loss given non-payment (recall $l(.)$ is monotone decreasing). This can become large if the margin we set in the previous period is not large enough to absorb the security price shock on the loser side. To avoid gap loss, this suggests a margin setting strategy with slowly changing, large margins. In fact, the optimal margins that minimize gap risk are infinite. This is clearly unrealistic, clients want as low operating margins as possible, and they would migrate to competitors who offer lower margins. We address this issue of competition in the next subsection.

3.6. Formulation as a stochastic control problem

In the previous subsection, we offer some time-local intuition on optimal margin setting. Within the multi-step framework, we present in this paper, margin setting is a dynamical problem. The margin we set in any given period affects the margins we can set in the future. Now we give a stochastic control formulation. We want to minimize the discounted penalized expected overall gap loss over infinite horizon

$$EL = E\left[(1-\delta)\sum_{t=0}^{\infty}\delta^t(EL_t + \mu_t M_t)\right] \tag{11}$$

given the evolution of the dynamic variable $A_{t+1} = M_t - |\Delta F_{t+1}|$, by choosing the M_t control variables, given information up to and including the time A_t is revealed. Here, $0 < \delta < 1$ is the single-period discount factor. The $\mu_t M_t$ penalty terms ensure that the unrealistic high margin solutions are not optimal, and they represent the competitors' pressure towards lower margins. In the Appendix, we derive an intuitive closed form for the μ_t coefficients, at this point, we can treat them as exogenously given.

Let $V_t(A_t)$ be the value function of the stochastic control problem. This is the value of the discounted (penalized) expected lifetime gap loss under the optimal margin setting policy, starting at period t, given the value of the loser account A_t. As the price shocks are

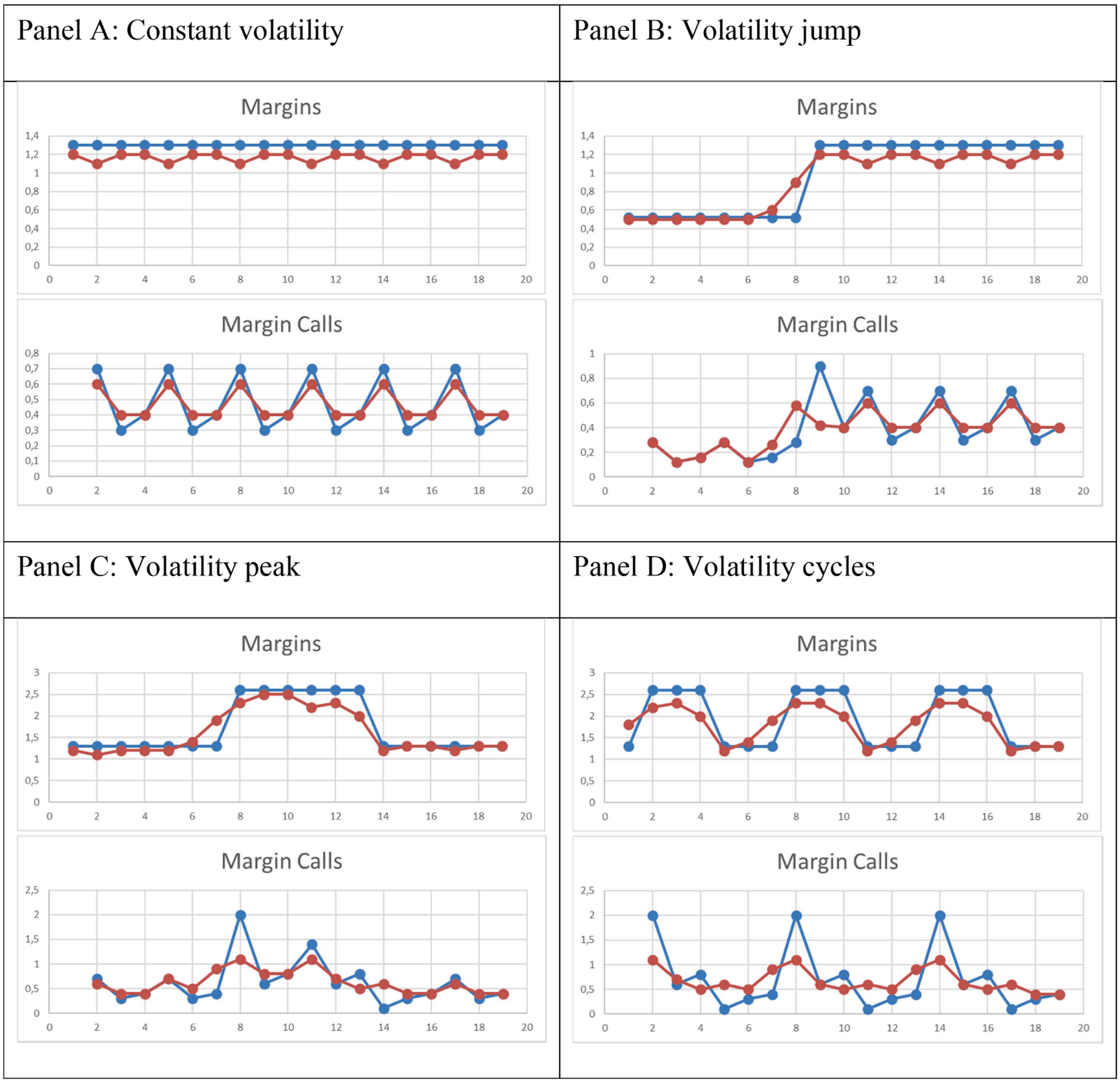

Fig. 1. Optimal margins under different volatility scenarios.
Note: Blue (red) dots indicate optimal risk sensitive (countercyclical) margin settings under different volatility scenarios. Margin level and margin calls are shown in percentage of the volatility level for 20 periods based on predefined volatility evolution.

independent, the Bellman equation yields the recursive relationship:

$$V_t(A_t) = \min_{M_t}\{\delta E[V_{t+1}(A_{t+1})] + (1-\delta)(EL_t + \mu_t M_t)\} \tag{12}$$

The optimal margin setting policy is given as the M_t value that minimizes the right-hand side in the Bellman equation.

$$M_t^{opt}(A_t) = \underset{M_t}{\mathrm{argmin}}\{\delta E[V_{t+1}(A_{t+1})] + (1-\delta)(EL_t + \mu_t M_t)\} \tag{13}$$

Substituting our model specifications (3) and (9) to the Bellman Eq. (12), we get

$$V_t(A_t) = \min_{M_t}\left\{\delta E[V_{t+1}(M_t - |\Delta F_{t+1}|)] + (1-\delta)\left(\lambda(M_t - A_t)^+ * \sigma_{t+1} * l\left(\frac{A_t}{\sigma_{t+1}}\right) + \mu_t M_t\right)\right\} \tag{14}$$

We solve this equation numerically. The $V_t(.)$ functions are represented on a dense grid of possible A values, i.e., as a vector. If the $V_{t+1}(A)$ vector is already known, the Bellman equation can be solved for $V_t(A)$ by numerical optimization in terms of the margins $M_t(A)$. With this numerical recursion procedure, we obtain both $V_t(A)$, the value function (vector) at time t, and as a byproduct, $M_t(A)$, the margin setting policy. In all our scenarios we investigated, we assumed a deterministic volatility scenario after the explicitly calculated last period. We calculated the value function for this last period by applying the numerical recursion procedure many times, until convergence was reached. After that, the numerical recursion procedure was used repeatedly, now with the time-dependent scenario volatilities, to obtain the value function and the optimal margins for earlier times.

4. Results

We solve the stochastic control problem of dynamical margin setting numerically for a few different volatility scenarios. In each case, we use the same series of IID standard normals to simulate the security price fluctuations, and then scaled them up with the volatilities.

All panels in Fig. 1 show the same quantities in the same format, for different scenarios. All curves are time series for about twenty periods. In the upper graph in each panel, the blue curve shows the margins set by the pure risk sensitive benchmark strategy, while the red curve is the optimal margin series set by our adaptive, countercyclical strategy. In the lower graphs the margin calls are shown for the benchmark (blue) and for the countercyclical (red) strategies.

In the first scenario, volatility is kept constant, our results in this case are summarized in Panel A. The benchmark margin level is constant, as it is just a multiple of the constant volatility. The countercyclical strategy produces a mildly fluctuating margin series, and it is somewhat lower than the benchmark. Indeed, the countercyclical strategy produces more tempered margin calls than the benchmark strategy; it tends to be "more forgiving". In case of a large security price shock, it demands a lower margin from the loser, thereby giving a chance for the account to recuperate, rather than exacerbate the problem. Due to this flexibility, the dynamic strategy can be competitive with lower margins than the benchmark.

In the second scenario (see Panel B), the volatility abruptly increases at the ninth period, as the proportional benchmark margin curve (blue) shows. The countercyclical strategy exhibits foresight – it starts raising the margin gradually (red curve) before the volatility shock. In our model, we assumed reliable volatility forecast, and the adaptive countercyclical strategy can take advantage of this information. As a result, the margin calls, especially close to the volatility shock, are much smaller for the adaptive strategy than for the benchmark.

In the third scenario (see Panel C), volatility jumps up, and later it returns to its initial lower value, as the proportional benchmark margin curve shows. The countercyclical strategy again produces a much-smoothed margin curve, and this results in less demanding margin calls.

The fourth scenario (see Panel D) shows cyclical variation of volatility. The benchmark margins, being proportional to volatility, are clearly procyclical. This produces large margin calls at volatility jumps. The smoothing and forecasting nature of our adaptive strategy moves the margin time series towards a countercyclical behavior that results in less severe margin calls.

In the above numerical examples, we assumed deterministic volatility scenarios. In practice, there can be several potential scenarios of future volatility paths, and the central counterparty should consider the most relevant ones. In particular, it should assess whether a recent shock was just a small and temporary jump in the prices or the start of long-lasting and heavy turbulences. To generate volatility scenarios, the central counterparty can rely on expert opinions and different techniques like time-series analysis (Brailsford and Faff, 1996; Asai et al., 2020), stochastic (macro)economic modelling (Ma et al., 2022), and machine learning tools (Mesquita et al., 2024).

5. Conclusion

This paper contributes to the existing literature on optimal margin setting policies of a central clearing counterparty (Longin, 1999; Murphy et al., 2016; Berlinger et al., 2019b) by modelling the losses of the CCP in a multiperiod model. Our model captures the trade-off between the higher loss absorption potential of higher margins and higher default probability of the clients in the case of frequent and large margin calls. We prove that an optimal margin setting takes into account recent price shocks and is more cautious in increasing margin level after a large price shock, hence the optimal policy is adaptive, smoothing out the volatility shocks. The efficiency of the method depends on whether reliable volatility scenarios are available and utilized. If volatility paths are given, there is no need to set artificially high margins during calm market conditions, when volatility shocks are improbable. In this case, the CCP can react to the market changes gradually, and in advance of forecasted volatility shocks, without overreacting temporary volatility spikes. In the case of rapid periodic volatility turbulences, the methodology yields countercyclical behavior.

CRediT authorship contribution statement

Edina Berlinger: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Zsolt Bihary:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Barbara Dömötör:** Writing – original draft, Investigation, Conceptualization.

Declaration of competing interest

We, authors of the paper “Dynamic margin optimization”, declare that there is no competing interest to declare.

Data availability

Data will be made available on request.

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Appendix: Calibration of the penalty coefficients

In our model specification, the penalty coefficients μ_t seem rather arbitrary, unlike the other parameters that can all be directly connected to observables. In this section, we will calibrate μ_t to a benchmark strategy.

The benchmark strategy observes σ, the security volatility for the next period, and assumes it stays constant for the foreseeable future. Under this assumption, the strategy sets a fixed margin m that optimizes the penalized expected gap loss in the long run. This strategy does not depend on the account level A_t. As the strategy assumes a time-homogeneous future, it essentially minimizes the expected penalized one-period loss:

$$EL_1 = E[\lambda|\Delta F_{t-1}|(m - |\Delta F_{t-1}| - \Delta F_t)^-] + \mu m =$$

$$= E[\lambda\sigma|s|(m - \sigma|s| - \sigma z)^-] + \mu m =$$

$$= \lambda\sigma^2 E\left[|s|\left(\frac{m}{\sigma} - |s| - z\right)^-\right] + \mu m =$$

$$EL_1 = \lambda\sigma^2 f(m/\sigma) + \mu m \tag{A.1}$$

where s and z are IID random variables, both following the distribution of ε, and $f(.)$ is the function

$$f(x) = E[|s|(x - |s| - z)^-] \tag{A.2}$$

Let us assume that $f(.)$ is well-behaved, differentiable, and convex. In this case, $EL_1$is also convex in m, and has a unique minimum that we can obtain by differentiation. This yields the equation

$$\mu = -\lambda\sigma f'(m/\sigma) \tag{A.3}$$

For a given set of model parameters, the solution of this equation yields the constant margin set by the benchmark strategy. Turning it around, we use the equation to calibrate the value of μ. If we observe a consensus margin m set by our competitors who (perhaps subconsciously) follow the benchmark strategy, it provides the coefficient for the penalty term in our more sophisticated strategy. In this sense, μ represents a measure of pricing pressure on the margin from our competitors. Indeed, the standard industry practice has been to set the margin at some multiple of the estimated volatility: $m = \alpha\sigma$ where α depends on a given percentile of the random change. In the case of normality assumption at a significance level of 99.5 %, it is a number in the vicinity of 2.6. Plugging in, we finally obtain the simple relation:

$$\mu_t = -\lambda\sigma_t f'(\alpha) = \lambda g \sigma_{t+1} \tag{A.4}$$

where at any given consensus α value, g is just a real number. If $\alpha = 2.6$, then $g = 0.1042$. Although the benchmark strategy in spirit assumes a time-homogeneous future, it still upgrades the margin based on the changing estimation for σ_{t+1}. Accordingly, we use time-dependent μ_t in our model, as the final equation shows.

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