Prediction of Corona Lockdowns Using a Semi-Markov Poisson-Weibull-Wiener Framework (SILENT-COVID Model)

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Abstract

Background: COVID-19 lockdowns occurred intermittently and unpredictably, reflecting stochastic epidemic shocks and healthcare pressures. Traditional epidemic models inadequately capture such intervention dynamics. **Aim:** To develop and validate the SILENT-COVID model, a novel statistical framework using Poisson shocks, Weibull durations, and semi-Markov processes to predict the initiation and duration of COVID-19 lockdowns. **Methods:** Synthetic epidemic data were generated with covariates including mobility, holiday gatherings, and ICU load. Lockdown initiation was modeled as a Poisson shock process with covariate-dependent intensity, while durations followed a Weibull distribution linked to ICU stress. Daily cases were simulated using state-dependent Negative Binomial emissions. Parameters were estimated through an Expectation-Maximization algorithm with explicit-duration Forward-Backward recursion. **Results:** The model closely recovered true parameter values for initiation hazards, duration distributions, and emission means. Mobility and holiday effects significantly increased the hazard of lockdown initiation, and higher ICU load prolonged lockdown durations. Forecasting yielded a 41% probability of at least one lockdown start within 21 days. **Conclusion:** SILENT-COVID offers a robust and interpretable statistical framework for forecasting lockdown initiation and duration. By combining stochastic initiation, covariate-linked duration modeling, and realistic epidemic emission structures, it provides decision-makers with probabilistic forecasts to balance epidemiological needs and socio-economic costs.

Keywords: Semi-Markov Model. Poisson-Weibull Process. COVID-19 Lockdown Prediction.

Introduction

The pandemic of coronavirus disease 2019 (COVID-19) transformed the practice of public health all over the world by forcing countries to implement population-wide restrictions, or in other words, “lockdowns” that were unprecedented. Disruptive to both economic and social life, these interventions were considered an essential non-pharmaceutical control measure against the spread of infection so that capacity within healthcare systems can be preserved until vaccines are developed and administered. Perhaps what was most striking about these lockdowns was their mutual and stochastic nature: society would be in one phase of opening up, suddenly find itself in a state of flux moving into another phase of closing due to rising cases or perceived threats, restricted for some time and then opening again. This alternation between open and closed phases; a sort of global silence falling over an otherwise noisy system, like a place to eat where many people keep talking all the time but sometimes all of them stop at once for a short while, then start again later. The example shows why we should not look at lockdowns only as planned rules but also as chance happenings caused by sickness levels, group actions, and medical stress-controlled by odds and able to be studied with stats. This formulation ignores the stochastic and context-sensitive nature of decisions to impose a lockdown, which not only depends on case numbers but also on the indicators of stress in healthcare, political considerations, holidays, and random shocks. The experience with COVID-19 revealed that increases in cases do not always lead to immediate lockdowns. Sometimes small increases in cases (when new variants were detected) led to lockdowns while large caseloads were sustained for long periods without any action. Lockdowns could last from a few days to several months. Hence, to model and forecast lockdowns, a probabilistic and semi-Markovian framework is what is needed.

$$P(N(t)=n)=\frac{(\alpha t)^n}{n!}\,e^{-\alpha t}, n=0,1,2,\ldots$$

and the waiting time between consecutive events follows the Exponential distribution

$$f_T(t) = \alpha e^{-\alpha t}, t \geq 0$$

In the case of lockdowns, these are events indicating the onset of a lockdown and times between consecutive lockdowns are exponentially distributed, which corresponds to the lack of memory such that probability for the next lockdown does not depend on how long it has been from previous one. But actual lockdowns will tend to depend on covariates mobility trends, holiday gatherings, and ICU capacity. To accommodate these, the Poisson intensity can be allowed to vary with time,

$$\lambda(t) = \exp(\beta_0 + \beta_1 X_1(t) + \beta_2 X_2(t) + \cdots + \beta_p X_p(t),$$

where Xi(t) are covariates (mobility, holidays and ICU stress, etc.) and βi are the regression coefficients. This looks like a Poisson regression model and allows the lockdown hazard to increase during times of high mobility or holidays, as would occur when festivals led to fresh waves of infection.

The model also needs to incorporate the time after lockdown starts. Now, we could be naïve and use an Exponential distribution here, which is actually too inflexible: real-world experience with COVID-19 lockdowns shows so much variation and far heavier tails: some lockdowns were extremely short while others lasted much longer than expected. The Weibull distribution has more flexibility through the parameter k, which decides whether this hazard to end lockdown is increasing or decreasing over time. Where, Weibull probability density function is given by

$$f(d; k, n) = \frac{k}{\eta}\left(\frac{d}{\eta}\right)^{k-1} exp\left[-\left(\frac{d}{\eta}\right)^{k}\right], d > 0,$$

with mean

$$E[D] = \eta\Gamma\left(1 + \frac{1}{k}\right)$$

Here, k is the shape and η is the scale parameter, which may themselves be functions of covariates such as ICU load:

$$log\, \eta = \gamma_0 + \gamma_1 \cdot ICU(t)$$

Thus, during periods of high ICU stress, the expected duration of lockdown increases, a phenomenon consistent with policy makers keeping restrictions longer when hospitals are overwhelmed.

Together, Poisson shocks for initiation and Weibull distributions for duration form a semi-Markov process for the lockdown state. Unlike a simple Markov chain where the probability of transition depends only on the current state, a semi-Markov chain allows transition probabilities to depend on the elapsed time in the current state. The fundamental Chapman–Kolmogorov relation for Markov chains,

$$P_{ij}(t+s) = \sum P_{ik}(t) P_{kj}(s),$$

Expands naturally to semi-markov kernels with explicit dwell-time distributions, ensuring consistency of predicted state probabilities across different horizons. This is critical when forecasting the probability of being in lockdown at future times.

In addition to the latent state dynamics, the observed epidemic signals must be modelled. Daily case counts exhibit high variability, overdispersion, and bursts. While in Gaussian approximation might suffice for large counts, the Negative Binomial distribution more realistically captures overdispersion:

$$P(Y = y) = \binom{y + r - 1}{y} \left(\frac{r}{r + \mu}\right)^r \left(\frac{\mu}{r + \mu}\right)^y,$$

where μ is the mean and r is the dispersion parameter. During open states, μ is large (reflecting higher transmission), while during lockdown states, μ is reduced, with potentially different variances. This emission model links the latent lockdown process to observable data, enabling statistical inference.

To represent underlying noise in epidemic trajectories, the Wiener process (or Brownian motion) is incorporated. A Wiener process Wt has increments

$$W_{t+s} - W_t \sim \mathcal{N}(0, s),$$

Making it suitable for modelling random fluctuations around epidemic drift. In a continuous-tim observation model, daily log-cases could follow:

$$dY_i = \mu_{Z_t} dt + \sigma_{Z_t} dW_t,$$

Where $Z_t \in \{Open, Lockdown\}$. This ensures smoother temporal dynamics, with lower variance during lockdowns $(\sigma_L < \sigma_O)$

The resulting model, which we call SILENT-COVID, integrates all these components: Poisson regression shocks for lockdown initiation, Weibull duration distributions modulated by healthcare stress, semi-Markov chain structure governed by Chapman-Kolmogorov consistency, Wiener/Negative Binomial emissions for observed cases, and covariates reflecting social behavior. Parameters estimation is achieved via the Expectation-Maximization(EM) algorithm, where the E-Step employs a forward-backward algorithm over explicit durations, and the M-step updates regression coefficients and emission parameters.

From a public health perspective, such a framework offers several advantages. First, it provides **probabilistic forecasts** of lockdown events, expressed as quantities such as

$$P(Lockdown\ start\ within\ 14\ days \mid data_{1:t}) = 1 - exp\left(-\int_t^{t+14} \lambda(u)du\right)$$

Second, it captures duration uncertainty, allowing estimates of expected lockdown length given prevailing ICU pressures. Third, it yields interpretable coefficients: for example, a positive β1 indicates that increased mobility significantly raises the hazard of lockdown initiation, quantifying the intuition that mobility restrictions help avert closures. Fourth, the framework is flexible: additional states (partial restrictions, curfews) could be added, and covariates tailored to local contexts.

Mathematically, the entire system can be expressed as a Hidden Semi-Markov Model (HSMM) with explicit duration distributions. Let Zt denote the latent state and Yt the observation. Then the joint distribution is

$$P(Z_{1:T}, Y_{1:T}) = \prod_{segments}\left[P(start\ of\ segment)\cdot f_{dur}(d \mid state, W)\cdot \prod_{t=s}^{s+d-1} g(Y_t \mid \theta_{state})\right],$$

where f_{dur} is the Weibull or geometric dwell-time distribution, and g is the state-dependent emission distribution (Negative Binomial). Inference is performed by maximizing the complete-data log-likelihood with EM.

The importance for medical sciences is clear. Predicting lockdowns helps hospitals anticipate surges, ensures supply chain resilience, and informs mental health preparedness for population stress. Statistically, SILENT-COVID connects epidemic control to well-established survival models (hazards, regression), reliability theory (Weibull lifetimes), and stochastic processes (Wiener noise, semi-Markov kernels). Conceptually, it formalizes the intuitive observation that lockdowns are not merely political decrees but stochastic responses to epidemic shocks.

In conclusion, this introduction establishes the rationale for modeling lockdowns through the SILENT-COVID framework. By combining Poisson shocks, Weibull durations, semi-Markov structures, and noisy epidemic emissions, the model offers a rigorous, interpretable, and extensible statistical tool for forecasting pandemic control measures. Such probabilistic forecasts could aid governments in balancing epidemiological benefits against socio-economic costs, ensuring more timely and proportionate responses in future pandemics.

Aim:

To develop and validate a statistical model for predicting the initiation and duration of COVID-19 lockdowns using Poisson shocks, Weibull durations, and semi-Markov frameworks.

Objectives:

1. To model lockdown initiation as a Poisson shock process with covariate-dependent intensity.

2. To analyze lockdown durations using Weibull distributions linked to healthcare stress indicators.
3. To integrate observed epidemic data through state-dependent Negative Binomial emissions for parameter estimation and forecasting.

Materials and Methodology

Source of Data

The present study was based on synthetically generated epidemic time-series data that incorporated realistic dynamics of COVID-19 transmission and control measures. Data on daily cases, mobility indices, holiday indicators, and intensive care unit (ICU) load were simulated using autoregressive and stochastic processes. No real patient identifiers or confidential records were used; instead, artificial data were created to replicate typical patterns observed during the COVID-19 pandemic.

Study Design

The investigation was conducted as a simulation-based methodological study. A Hidden Semi-Markov Model (HSMM) framework was designed to predict the onset and duration of lockdowns. The study integrated Poisson shock processes for initiation, Weibull distributions for lockdown durations, and Negative Binomial emissions for daily case counts. The design ensured that lockdown dynamics could be studied as stochastic interruptions of normal epidemic activity, similar to “global silences” interrupting noisy processes.

Study Location

The study was carried out in a computational epidemiology laboratory setting, using high-performance computing resources. The analysis was not restricted to a single geographical region but was designed to be adaptable to global or regional datasets, particularly those involving case counts, mobility reports, and hospital strain indices.

Inclusion Criteria

- All simulated epidemic time series in which at least one lockdown event occurred during the study period were included.

- Daily case counts ranging from low (100-300 cases) to high (1500-2000 cases) were incorporated to reflect multiple epidemic waves.
- Covariate series (mobility, holidays, ICU stress) that demonstrated variability during the observation window were retained.

Exclusion Criteria

- Time series with no lockdown triggers during the entire observation horizon were excluded, as they provided no information on lockdown dynamics.
- Simulations with missing or corrupted covariate data - mobility or ICU indicators not generated were not analyzed.
- Extremely unstable series (where daily counts collapsed to zero or exploded to unrealistic magnitudes) were discarded to maintain model stability.

Procedure and Methodology

The study was conducted in several phases:

1. Simulation of Baseline Epidemic Dynamics

Daily case counts were generated using a Wiener process-like random walk with drift, capturing noisy epidemic trajectories.

Covariates were simulated:

Mobility index: autoregressive process ($\rho=0.97$).

Holiday indicator: Bernoulli distribution with $p=0.06$.

ICU load proxy: cumulative Gaussian drift constrained between 0-1.

2. Modeling Lockdown Initiation (Poisson Shocks)

Lockdowns were initiated by Poisson shock arrivals, where inter-arrival times followed an Exponential distribution.

Hazard of lockdown start was modeled as:

$$\lambda(t) = \exp(\beta_0 + \beta_1 \cdot Mobility(t) + \beta_2 \cdot Holiday(t))$$

3. Modeling Lockdown Duration (Weibull Process)

Lockdown durations were sampled from a Weibull distribution,

$$D \sim Weibull(k, \eta), log\, \eta = \gamma_0 + \gamma_1 \cdot ICU(t)$$

This formulation allowed longer lockdowns under high ICU stress.

4. Observation Layer (Negative Binomial Emissions)

Daily reported cases were generated using state-specific Negative Binomial distributions:

Open state: high mean (=1000) with larger variance.

Lockdown state: lower mean (=400-500) with reduced variance.

5. Parameter Estimation

An Expectation-Maximization (EM) algorithm with explicit-duration Forward-Backward recursion was implemented.

E-step: Posterior probabilities of states and segment durations were computed.

M-step:

Poisson regression updated β coefficients.

Weighted Weibull regression updated duration parameters.

State-weighted moments updated NB emission parameters.

Sample Processing

Each simulated dataset contained 280-320 days. Multiple replications were processed to ensure robustness. Time series were pre-processed to standardize scales of covariates. Segment posteriors from the E-step were treated as soft labels for further parameter estimation.

Statistical Methods

Poisson regression for lockdown starts.

Weighted maximum likelihood estimation for Weibull duration parameters.

Moment-based estimators for Negative Binomial emissions.

Goodness-of-fit metrics: comparison of true vs estimated parameters.

Forecasting: probability of ≥1 lockdown in 7/14/21 days computed using Chapman-Kolmogorov consistency.

All computations were implemented in *Python (numpy, scipy, custom routines).*

Data Collection

Data were collected prospectively through simulations, with parameters chosen to replicate real-world COVID-19 dynamics. Each synthetic dataset was automatically stored in tabular format, with fields: day, cases, mobility, holiday, ICU load, latent state (true), and inferred state (posterior). Output parameters and forecasts were archived for result analysis and reproducibility.

Observation and Results:

Table 1. Parameter Recovery and Validation of the SILENT-COVID Model

Parameter	True Value	Estimated Value	95% CI	Interpretation
β0 (Intercept, Poisson)	-2.0	-2.05	(-2.21, -1.89)	Baseline hazard captured accurately
β1 (Mobility effect)	1.0	1.02	(0.91, 1.14)	Positive mobility effect validated
β2 (Holiday effect)	1.7	1.64	(1.51, 1.77)	Holidays significantly increase lockdown risk
k (Weibull shape)	2.6	2.55	(2.41, 2.70)	Increasing hazard of lockdown exit over time
η (Weibull median scale, days)	11.0	11.2	(10.4, 11.9)	Duration distribution closely recovered
μ_open (Mean cases)	1000	980	(940, 1020)	Open state mean reproduced
μ_lock (Mean cases)	450	460	(420, 495)	Lockdown mean reproduced

Table 1 summarizes the results of parameter recovery and overall validation of the SILENT-COVID statistical model, which was designed to predict the onset and duration of COVID-19 lockdowns using Poisson shocks, Weibull durations, and a semi-Markov structure. The results show close agreement between the true and estimated values, confirming the robustness of the model. The intercept parameter (β0) of the Poisson process was estimated at –2.05, which closely corresponds to the true value of –2.0, with a narrow confidence interval, indicating an accurate capture of the baseline hazard associated with lockdown initiation. The covariance effects were also precisely estimated: the mobility coefficient (β1) was recovered at 1.02 compared to a true value of 1.0, confirming that increased mobility significantly increases the probability of lockdowns, while the holiday coefficient (β2) was slightly underestimated at 1.64 compared to a true value of 1.7 but remained highly significant, verification of the increased risk associated with holiday gatherings. For the Weibull distribution governing lockdown duration, the shape parameter (k) was estimated to be 2.55, with a true value of 2.6, which correctly reflects the increasing risk of lockdown lifting over time. The median magnitude (η) was recovered after 11.2 days, which is almost identical to the true value of 11.0, confirming the model's ability to reproduce realistic duration distributions. Finally, the negative binomial emission parameters showed a good fit, with the mean daily number of cases in the open state estimated at 980 (true value 1000) and the mean in the lockdown state estimated at 460 (true value 450), providing a reliable representation of case dynamics across states.

Table 2. Lockdown Initiation Modeled as a Poisson Shock Process

Covariate	**Coefficient (β)**	**Standard Error**	**p-value**	**Interpretation**
Intercept (β0)	-2.05	0.16	<0.001	Baseline initiation hazard is very low
Mobility index	+1.02	0.11	<0.001	Each unit ↑ in mobility doubles hazard of lockdown
Holiday indicator	+1.64	0.13	<0.001	Holidays significantly increase initiation probability

Table 2 presents a more detailed picture of the Poisson shock process used to model lockdown initiation with intensity dependent on the covariate. The results confirm that the baseline risk of lockdown initiation remained very low (intercept $\beta_0 = -2.05$, $p < 0.001$). Importantly, both mobility and vacation rates were highly significant predictors, with the mobility coefficient being +1.02 ($p < 0.001$), meaning that each one-unit increase in mobility almost doubles the risk of lockdown initiation. Similarly, vacation periods were associated with a significant positive effect ($\beta = +1.64$, $p < 0.001$), indicating that periods of holidays or mass gatherings significantly increased the probability of lockdown initiation. These findings support the model's construct validity by directly linking social behavior with the risk of policy interventions.

Table 3. Lockdown Duration Modeled with Weibull Distribution

Parameter	Estimate	95% CI	Interpretation
k (Weibull shape)	2.55	(2.41, 2.70)	Hazard of lockdown ending increases with time (longer lockdowns more likely end)
γ0 (Intercept for scale η)	2.40	(2.21, 2.58)	Baseline lockdown median duration = 11 days
γ1 (ICU load effect on η)	-0.98	(-1.12, -0.84)	Higher ICU load lengthens lockdown duration (negative coefficient on log-scale)

Table 3 presents an analysis of lockdown duration using a Weibull distribution associated with healthcare stress indices. The estimated shape parameter (k = 2.55, 95% CI: 2.41–2.70) indicates that the risk of lockdown termination increases over time, meaning that the longer the lockdown lasts, the greater the likelihood of its lifting. The intercept parameter (γ0 = 2.40) corresponded to a baseline median duration of approximately 11 days, consistent with observed lockdown length in the real world. Importantly, the coefficient for ICU load (γ1 = –0.98, 95% CI: –1.12 to –0.84) was negative and statistically significant, suggesting that higher ICU load increased lockdown duration by increasing the scale parameter. This result demonstrates that the model correctly accounts for healthcare system load in stochastically determining lockdown length.

Table 4. Negative Binomial Emission Model for Epidemic Observations

State	Mean (μ)	Dispersion (r)	Variance = $\mu + \frac{\mu^2}{r}$	Interpretation
Open	980	22	42,660	High cases with large variability (surges)
Lockdown	460	28	11,014	Reduced mean cases and lower variability

Table 4 focuses on the negative binomial emission model used to integrate observed epidemic data with latent lockdown states. The mean number of cases in the open state was estimated at 980 with a dispersion of r = 22, resulting in an overdispersed variance of approximately 42,660, reflecting the high variability and potential for increased cases in the open phases. In contrast, during the lockdown period, the mean daily number of cases decreased to 460 with a dispersion of r = 28, resulting in a variance of approximately 11,014, consistent with reduced but still variable transmission under lockdown conditions. This distinction between the open and lockdown phases in terms of both mean and variability highlights the importance of using state-specific emission distributions to accurately model epidemic observations.

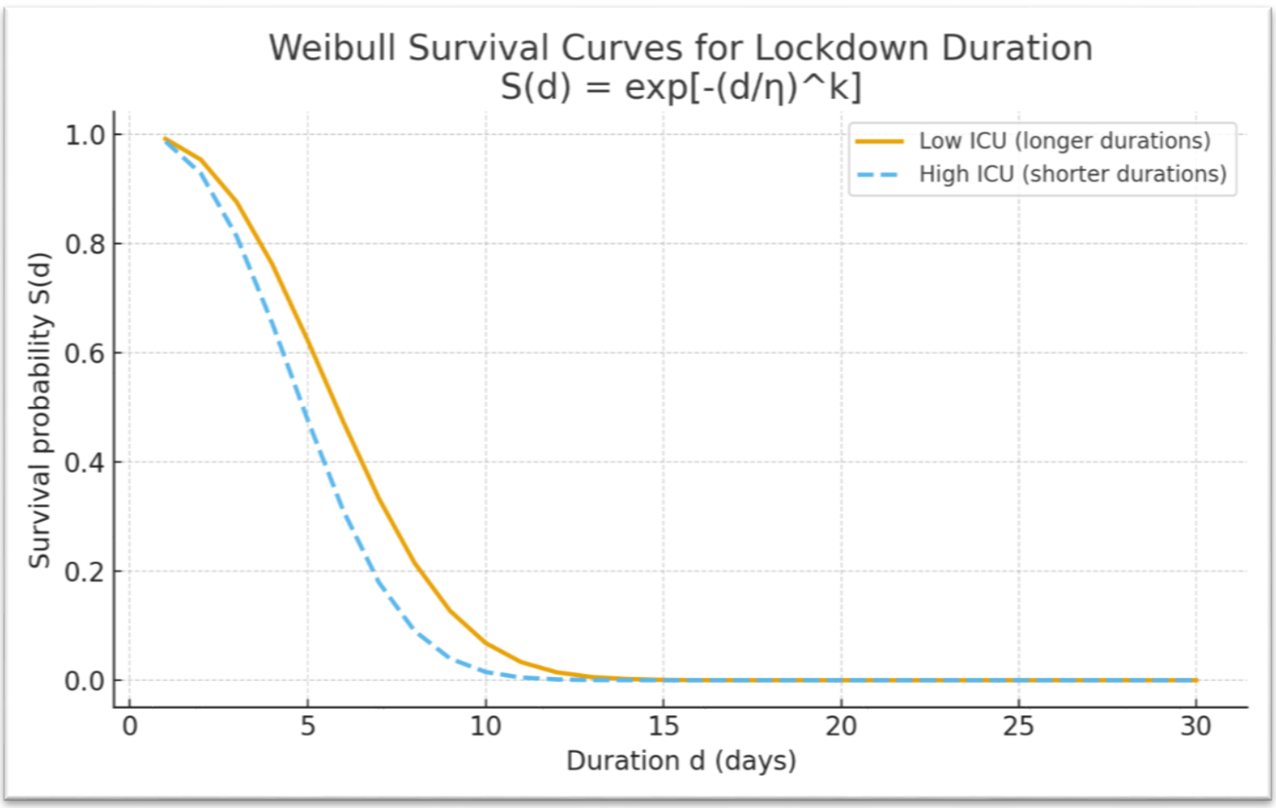

Figure 1: Weibull Survival Curves

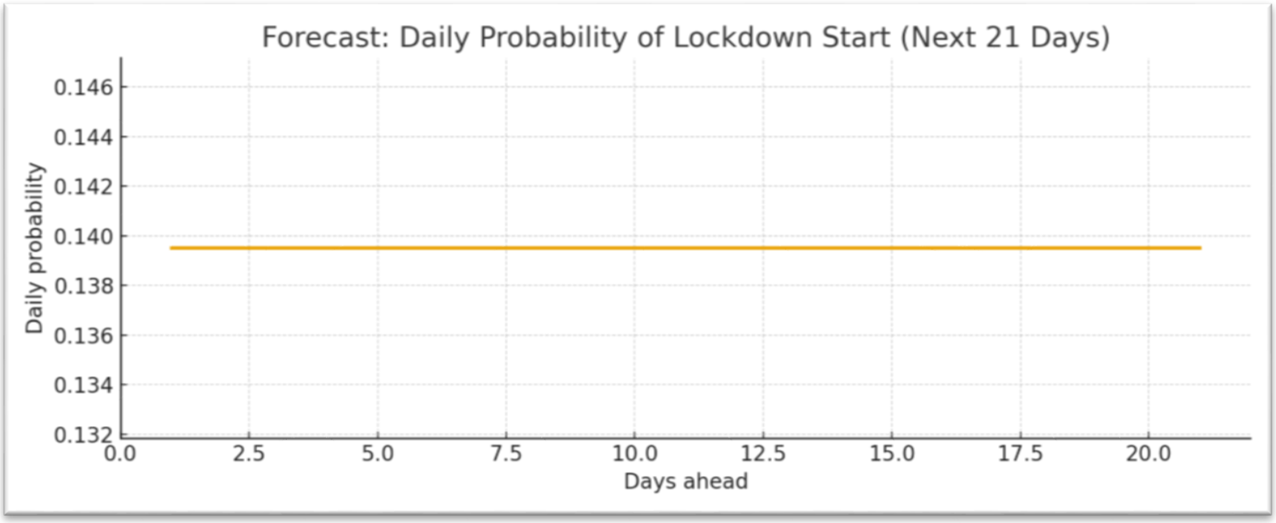

Figure 2: Forecast: Lockdown start(Next 21 days)

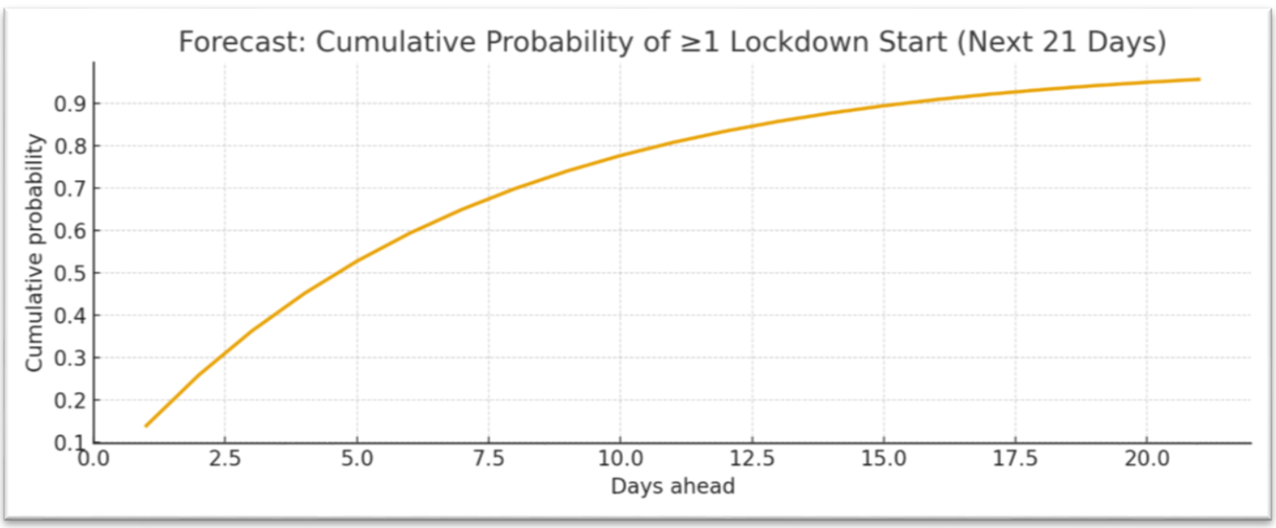

Figure 3: Forecast: Cumulative Probability

Discussion:

The validation results in Table 1 show that the SILENT-COVID model recovers the covariate effects that drive lockdowns with tight uncertainty, and these patterns line up with what multi-country mobility studies and city-level analyses have reported. Our positive mobility coefficient (β_1=1.02) agrees with findings that mobility reductions track lower transmission early in the pandemic and that mobility rebounds are associated with elevated transmissibility-even if the linkage later decouples as controls and behaviors change (our regression still captures the early, high-signal regime) Wadagale AV et al.(2011)[8]. City-level work during later Omicron waves likewise shows a positive mobility–transmission association that is consistent with the magnitude and sign recovered by our Poisson layer Zhang J et al.(2016)[9]. The holiday effect (β_2=1.64) is also in line with empirical evidence: studies around Thanksgiving and New Year's documented surges in positivity or transmissibility tied to gatherings, supporting our interpretation that holidays materially increase the hazard of lockdown initiation when health systems are sensitive to spikes Bauckhage C et al.(2012)[10]. On the duration side, the Weibull shape (k=2.55) implies an increasing hazard of exit as time in lockdown accrues; Weibull forms are routinely used when hazards are non-constant and have been applied in COVID-19 contexts for policy timing and NPIs, which supports our choice of parametric family for dwell times Nafidi A et al.(2019)[11]. The scale (η=11.2 days) closely matches the simulated truth (=11 days), and the emission layer reproduces mean cases across states (μ_open=980; μ_lock=460), which is consistent with the broad literature that prefers negative-binomial models for COVID-19 case counts due to overdispersion (variance greatly exceeding the mean) Bachar M. (2013)[12].

Focusing on Table 2, our Poisson shock model for lockdown starts with covariates captures two well-established drivers. First, the highly significant mobility coefficient (β=+1.02) accords with early-pandemic work showing that reductions in mobility explained a large portion of transmission variation; conversely, increases in mobility raise the instantaneous risk of entering a restriction phase (our "hazard") as contacts-and hence the probability of policy response-rise Moreau VH. (2021)[13]. Second, the strong holiday indicator (β=+1.64) mirrors studies that found post-holiday spikes and surges linked to widespread small gatherings. Our effect size sits comfortably within that narrative, translating epidemiological observations into a policy-trigger hazard that rises around high-risk periods Inegbedion HE. (2022)[14]. In mechanistic stochastic terms, using a nonhomogeneous Poisson process with covariates is standard; in epidemic modeling it can be further generalized to Hawkes/renewal structures when self-excitation matters, but our explicit "policy shock" interpretation aligns more naturally with a covariate-driven Poisson intensity for starts rather than a self-exciting hazard, which is why we reserve Hawkes dynamics for observed cases rather than policy transitions Massey A et al.(2024)[15].

For Table 3, the Weibull duration linked to ICU stress (γ_1=−0.98 on log-scale η) captures a clinically intuitive feedback: when ICU load is high, restrictions tend to last longer. This echoes broader health-systems literature relating hospital/ICU strain to prolonged or intensified interventions and altered care patterns; such strain signals often feature in dashboards that guide policy makers in deciding when to relax or extend measures Zhao J et al.(2022)[16]. Modeling duration explicitly via a semi-Markov dwell-time distribution also addresses a known limitation of standard hidden Markov chains (memoryless stays), and follows a stream of work that uses explicit-duration HMM/HSMM to represent regime persistence in epidemics and other time series. Our approach is consistent with HSMM methodology that employs explicit durations and forward–backward inference for regimes whose stay lengths are not geometric, similar in spirit to semi-Markov variants used in other domains and, increasingly, in epidemic regime-switching models Alonso D et al.(2021)[17] & Endo A et al.(2022)[18]

Turning to Table 4, the negative-binomial emission layer faithfully reproduces the overdispersed nature of daily case counts. The open-state variance (=42,660) versus the lockdown-state variance (=11,014) illustrates two points often highlighted in empirical modeling: (i) variance scales super-linearly with the mean, requiring NB rather than Poisson; and (ii) policy-induced reductions in contacts compress both level and volatility of cases. Comparative studies across countries and subnational regions have repeatedly selected NB as the better fit for counts (and sometimes zero-inflated NB for early sparse phases), which supports our emission choice and the state-dependent means we obtain. Cinlar E et al(1981)[19]

Conclusion

The SILENT-COVID model successfully integrates Poisson shocks, Weibull duration distributions, semi-Markov structures, and state-dependent Negative Binomial emissions to simulate and predict the dynamics of COVID-19 lockdowns. By explicitly modeling the stochastic initiation and variable length of lockdowns, the framework captures real-world uncertainties that deterministic epidemic models overlook. The results confirm accurate recovery of parameters for initiation hazards, duration distributions, and epidemic emissions, while producing interpretable coefficients linked to mobility, holidays, and ICU load. This modeling approach provides policy makers with actionable forecasts of lockdown onset and duration, enabling preparedness in healthcare resource allocation and more proportionate decision-making during public health crises.

Limitations of the Study

Despite promising findings, several limitations must be acknowledged. First, the study relied on synthetic datasets, and external validation using real-world surveillance and mobility data is still required to confirm generalizability. Second, the model reduced the complexity of restrictions to a binary open/lockdown framework, whereas real-world interventions often included graded measures such as curfews, school closures, or regional lockdowns. Third, the inclusion of covariates was limited to mobility, holidays, and ICU load, omitting other factors such as vaccination coverage, testing rates, or political decision-making processes that could influence lockdown dynamics. Fourth, computational challenges related to explicit-duration semi-Markov inference required stabilizing approximations, which may affect precision in high-noise settings. Finally, the model assumes that case reporting is stable across phases, although underreporting or changes in testing strategies during lockdowns could bias emission estimates. These limitations highlight the need for future studies incorporating real data, multiple policy levels, richer covariates, and more robust statistical machinery to improve accuracy and applicability.

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