Counting Famichikis

A Cox–Hawkes model of convenience-store fried-chicken demand, rebuilt from public data

An unofficial fan project, not affiliated with FamilyMart Co., Ltd.

Abstract. FamilyMart has sold more than 2.9 billion Famichikis since 2006 but publishes no store-level sales. We reconstruct a real-time estimate for the 16,202 stores listed in FamilyMart's online store finder from public inputs: the official store directory, live JMA AMeDAS weather, the public-holiday calendar and published sales milestones. Expected volume is allocated by a Huff-type attraction model, shaped by store-type intraday profiles masked to opening hours, and modulated by hinge-type temperature and rain responses in the spirit of the breakpoint models used for convenience-store POS data. Individual sales are drawn from a mean-preserving *Cox–Hawkes* process: a log-normal Ornstein–Uhlenbeck modulation of national demand, gamma store-day heterogeneity that makes daily store counts negative binomial, and self-exciting follow-up purchases. Offline validation of the production code reproduces the national target within 0.1%, matches a closed-form overdispersion prediction (8.72 observed vs. 8.71 predicted), and yields bursty inter-purchase times (Goh–Barabási $B = 0.18$ vs. -0.01 for Poisson). Parameters are labelled *published*, *derived* or *assumed* according to their provenance.

1 Introduction

How many Famichikis are being sold right now, and where? FamilyMart's boneless fried chicken, cut from the *sai* part of the thigh and launched on 17 October 2006 at ¥140 in about 6,900 stores [1], passed 2 billion units in 2023 [2] and 2.9 billion in 2026 [3]. The company's own ordering AI forecasts each store from past sales, nearby foot traffic, weather and the calendar [4]; to our knowledge these data are not publicly available. This note asks how far public data alone can go, and how to give the estimate qualitative features reported for retail demand: heterogeneity across stores, dependence on time of day and weather, and clustering in time.

We contribute (i) a store-level demand model anchored to official totals (Section 4); (ii) a mean-preserving Cox–Hawkes sampler that turns rates into individual, bursty sales (Section 5); and (iii) closed-form dispersion results with an offline validation of the production code (Section 6).

2 Related work

Weather and retail. Badorf and Hoberg [5] fit random-coefficient models to daily sales of 673 brick-and-mortar stores and report weather effects that are non-linear, seasonal and store-specific. Steinker et al. [6] show that weather cuts daily sales-forecast errors of a large online retailer by 8.6–12.2% (up to 50.6% on summer weekends), and Murray et al. [7] link sunlight to higher spending. For Japanese convenience stores, the JMA [8] fits segmented regressions of POS sales on temperature and tests for *breakpoint temperatures* at which demand changes slope; we adopt the same hinge form.

Arrival processes. Kim and Whitt [9] report that service-system arrivals are consistent with non-homogeneous Poisson processes after careful conditioning, while pooled data tend to be overdispersed. Doubly stochastic (Cox) processes [10] and self-exciting (Hawkes) processes [11–13] are common extensions, and Goh and Barabási [14] give the burstiness coefficient we use as a diagnostic.

Retail counts. The M5 competition [15] illustrated that store–item unit sales tend to be hierarchical, intermittent and heterogeneous; DeepAR [16] models such counts with a negative-binomial likelihood. Our gamma store-day effect yields the same marginal distribution (Proposition 1).

Spatial demand. In Huff's model [17] the probability that a shopper picks a store decays with distance and grows with its attractiveness relative to the alternatives; it motivates our attraction weights.

Table 1. Inputs. published: taken from a source; derived: arithmetic on published figures.

Input	Refresh	Kind
Stores: location, hours, opening date [18]	rebuild	published
Temperature, rain at 594 stations [19]	10 min	published
Public holidays	12 h	published
National volume $\bar{N}$ [2, 3]	static	derived
Flavour mix, plain : Red [20]	static	published
Famichiki-Day lift [21]	static	derived

3 Data

Table 1 lists the inputs. Each store's type $k(i) \in \mathcal{K} = \{\text{street, station, office, hospital, campus, highway, airport}\}$ is inferred from its name (*eki* marks a station store), excluding "in front of" variants: 13,905 stores are street stores and 1,738 station stores. Each store is linked to its nearest AMeDAS thermometer. Figure 1 shows the result.

4 Store-level demand

4.1 National anchor

The series total rose from 2.0×10^9 (September 2023) to 2.9×10^9 (September 2026), so

$$\bar{N} = \frac{(2.9 - 2.0) \times 10^9}{3 \times 365} \approx 821{,}918 \text{ day}^{-1} \approx 9.5 \text{ s}^{-1}. \quad (1)$$

Over an estimated ≈15,400 fryer-equipped stores this is ≈53 per store per day, about five frozen bags of ten, consistent with the ~40 a day reported for a single campaign SKU [22].

4.2 Attraction and allocation

Definition 1 (Attraction). *Store i has attraction*

$$a_i = \tau_{k(i)}\, g(\rho_i)\, \eta_i\, \nu_i, \qquad g(\rho) = 0.85 + 0.35\, \frac{\min(\rho, 30)}{30}, \quad (2)$$

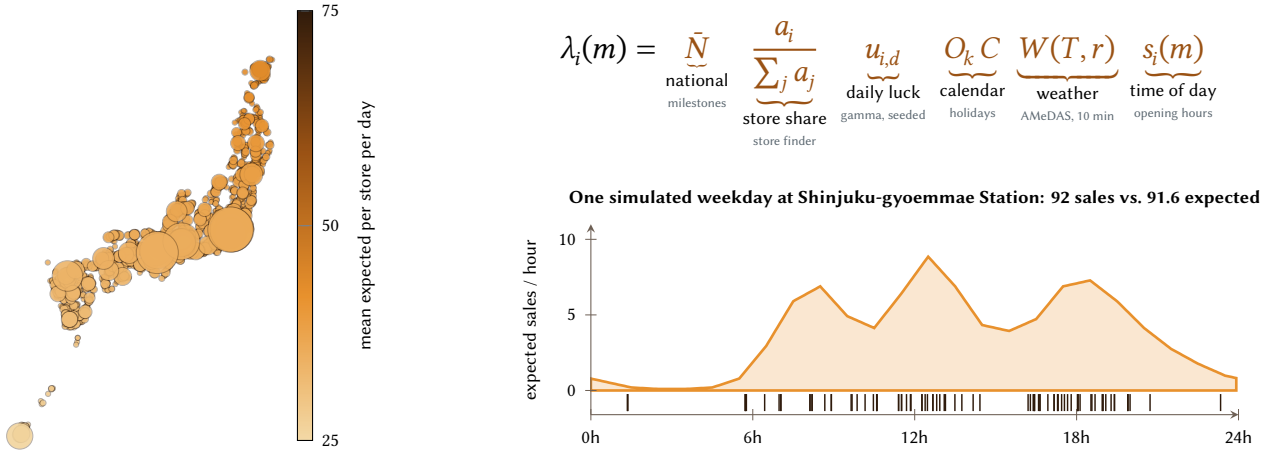


Figure 1. Left: the 16,202 stores pooled into ≈9 km cells; dot area grows with the number of stores, colour is their mean baseline volume D_i (Equation (3)). Right: the expected rate (5) factor by factor with its public input, and one simulated day at the busiest store: the shaded curve is λ_i, the ticks are the Cox–Hawkes sales of Section 5, clustered around lunch and in small bursts.

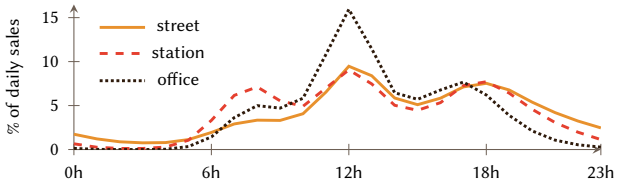


Figure 2. Intraday profiles c_k, aggregated to hours, for three of the seven store types.

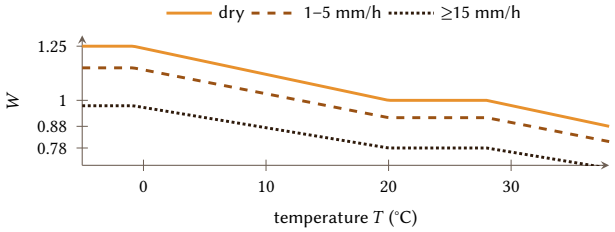


Figure 3. Weather response $W_T(T)\,W_r(r)$ (Equations (6) and (7)).

where τ_k is a type weight, ρ_i the number of FamilyMarts within ~3 km, $\eta_i = \min\{1, \ell_i/1440+0.2\}$ penalises short opening hours ℓ_i (in minutes), and $v_i = 0.85$ in a store's first year (1 otherwise).

The baseline daily volume is the attraction share of the anchor:

$$D_i = \bar{N}\,\frac{a_i}{\sum_j a_j}. \tag{3}$$

Remark 1 (Huff interpretation). In a Huff model [17] a shopper at x picks store i with probability $A_i\, d(x,i)^{-\gamma} / \sum_j A_j\, d(x,j)^{-\gamma}$. If stores are sited where demand is concentrated, local store density is a proxy for demand density. Integrating over a dense neighbourhood of near-symmetric competitors then gives a per-store share that increases with density at a diminishing rate, which the concave g approximates.

4.3 Intraday shape

Each type has hourly weights $h_k(0:23)$ (Figure 2). The assumed profiles peak around lunch; station stores reportedly take ~37% of sales before noon and street stores still ~10% overnight [23]. Treating $h_k(H)$ as the level at mid-hour, the minute profile is the linear interpolant $\tilde{c}_k(m)$, normalised to $c_k = \tilde{c}_k / \sum_m \tilde{c}_k(m)$. With an opening indicator $o_i(m)$, the store's share of its day in minute m is

$$s_i(m) = \frac{c_{k(i)}(m)\, o_i(m)}{Z_i}, \qquad Z_i = \sum_{m=0}^{1439} c_{k(i)}(m)\, o_i(m), \tag{4}$$

so a store open 7–23h still sells its full D_i. Summed over stores on a neutral weekday, expected national sales peak at 79 k in the 12:00 hour and bottom out at 5 k at 03:00.

4.4 Exogenous modifiers

For store i in minute m of day d, the expected rate (per minute) is

$$\lambda_i(m) = D_i\, u_{i,d}\, O_{k(i)}(d)\, C(d)\, W\big(T_{\sigma(i)}(m), r_{\sigma(i)}(m)\big)\, s_i(m), \tag{5}$$

where $\sigma(i)$ is the store's weather station, $O_k(d)$ a weekend-and-holiday factor (Table 2), $C(d) = 1.26$ on Famichiki Day (17 October) and 1 otherwise, and $u_{i,d}$ the store-day effect of Section 4.5. Weather enters as a product of hinges,

$$W_T(T) = \min\{1.25,\ 1 + 0.012\,(20 - T)_+\} \cdot \max\{0.88,\ 1 - 0.012\,(T - 28)_+\}, \tag{6}$$

$$W_r(r) = 1 - 0.08\,\mathbb{1}_{r\geq 1} - 0.07\,\mathbb{1}_{r\geq 5} - 0.07\,\mathbb{1}_{r\geq 15}, \tag{7}$$

with $W = W_T\, W_r$ (Figure 3). The breakpoints at 20 °C and 28 °C play the role of JMA's breakpoint temperatures [8]; the slopes are assumptions, chosen so that cooler days raise demand, a pattern reported for weather-sensitive categories [5].

4.5 Store-day heterogeneity

Stores have good and bad days beyond what the covariates explain. We draw $u_{i,d} \overset{\text{iid}}{\sim} \text{Gamma}(\kappa,\kappa)$ (mean 1, coefficient of variation $\kappa^{-1/2}$) from a generator seeded by the date, then rescale so that $\sum_i D_i u_{i,d} = \sum_i D_i$ and the national total is untouched.

Proposition 1 (Negative-binomial store days). *If $N_{i,d} \mid u \sim \text{Poisson}(\mu_i u)$ with $u \sim \text{Gamma}(\kappa,\kappa)$, then $N_{i,d} \sim \text{NB}\big(\kappa, \frac{\kappa}{\kappa+\mu_i}\big)$, with*

$$\mathbb{E}N_{i,d} = \mu_i, \qquad \text{Var}\, N_{i,d} = \mu_i + \mu_i^2/\kappa.$$

Table 2. Parameters and their provenance.

Parameter	Value	Kind
$\bar{N}$, national volume	821,918 / day	derived
τ_k: street, station, office	1.0, 1.5, 1.2	assumed
τ_k: hospital, campus	0.8, 0.8	assumed
τ_k: highway, airport	1.3, 1.4	assumed
O_k: street, station, office	1.08, 0.82, 0.30	assumed
O_k: hospital, campus	0.55, 0.40	assumed
O_k: highway, airport	1.35, 1.15	assumed
C on Famichiki Day	1.26	derived
W_T breakpoints; slope	20, 28 °C; 1.2%/°C	assumed
κ, store-day shape	8	assumed
s, θ^{-1}, modulation	0.15, 40 s	assumed
η, β^{-1}, self-excitation	0.35, 15 s	assumed
Flavour mix, plain : Red	53.3 : 14.8	published

Proof. Gamma–Poisson mixture: integrating Poisson$(n; \mu u)$ against the Gamma(κ, κ) density gives the negative-binomial pmf; the variance follows from $\operatorname{Var} N = \mathbb{E}\operatorname{Var}(N \mid u) + \operatorname{Var}\mathbb{E}(N \mid u) = \mu + \mu^2 \operatorname{Var} u$. □

This is the likelihood DeepAR uses for retail counts [16]; we set $\kappa = 8$ (CV ≈ 0.35).

5 From rates to individual sales

A non-homogeneous Poisson process with intensity (5) implies unclustered arrivals with Poisson counts, which is likely too regular: purchases plausibly cluster (groups buying together, a fresh batch from the fryer), and pooled arrival data tend to be overdispersed [9]. We therefore use a *Cox–Hawkes* process.

Definition 2 (Sale process). *Let X_t be a stationary Ornstein–Uhlenbeck process [24], $\mathrm{d}X_t = -\theta X_t\,\mathrm{d}t + s\sqrt{2\theta}\,\mathrm{d}B_t$, and $M_t = \exp(X_t - s^2/2)$, so $\mathbb{E}M_t = 1$. Sales at store i have conditional intensity (per second)*

$$\lambda_i^*(t) = (1-\eta)\,\lambda_i(t)\,M_t + \sum_{t_j^{(i)} < t} \eta\,\beta\,e^{-\beta(t - t_j^{(i)})}, \tag{8}$$

with branching ratio $0 \le \eta < 1$ and kernel rate β: a sale triggers, on average, η follow-up sales at the same store after $\mathrm{Exp}(\beta)$ delays.

We use $s = 0.15$, $\theta^{-1} = 40$ s, $\eta = 0.35$ and $\beta^{-1} = 15$ s.

Proposition 2 (Mean preservation). *If λ_i varies slowly relative to β^{-1}, then $\mathbb{E}\,\lambda_i^*(t) = \lambda_i(t)$; in particular the expected national total equals $\sum_i \int \lambda_i$, the anchored volume.*

Proof. By the cluster representation [12], immigrants arrive at rate $(1-\eta)\lambda_i M_t$ and each founds a Galton–Watson family of expected size $\sum_{g\ge 0}\eta^g = (1-\eta)^{-1}$. Taking expectations with $\mathbb{E}M_t = 1$ gives $(1-\eta)\lambda_i \cdot (1-\eta)^{-1} = \lambda_i$. □

Proposition 3 (Overdispersion). *For a stationary national rate Λ and window w, the Fano factor $F(w) = \operatorname{Var} N(w)/\mathbb{E}N(w)$ is approximately*

$$F(w) \approx \frac{1}{(1-\eta)^2} + \Big(1 - \frac{1}{(1-\eta)^2}\Big)\frac{1 - e^{-\gamma w}}{\gamma w} + \Lambda\big(e^{s^2} - 1\big)\frac{2(\theta w - 1 + e^{-\theta w})}{\theta^2 w}, \tag{9}$$

with $\gamma = (1-\eta)\beta$, and the Pearson dispersion of daily store counts satisfies $\mathbb{E}\big[(N_{i,d} - \mu_i)^2/\mu_i\big] \approx (1-\eta)^{-2} + \mu_i/\kappa$.

Table 3. Offline validation of the production sampler.

Statistic	Poisson	Cox–Hawkes
Mean rate at lunch (model 23.52 s^{-1})	23.51	23.60
Fano factor, $w = 1$ s	1.00	1.41
Fano factor, $w = 60$ s	1.06	19.7
Burstiness B of store gaps [14]	−0.01	0.18
Full weekday total (target 821,918)		821,084
Pearson dispersion (predicted 8.71)		8.72
Store-day count, 5th–50th–95th pct.		19 – 47 – 96

Sketch. The first line is the count variance of an exponential-kernel Hawkes process, whose covariance density decays at rate $(1-\eta)\beta$ [13]. The second is $\Lambda^2 \int_0^w \int_0^w \operatorname{Cov}(M_u, M_v)\,\mathrm{d}u\,\mathrm{d}v$ divided by Λw, using $\operatorname{Cov}(M_u, M_v) = e^{s^2 e^{-\theta|u-v|}} - 1 \approx (e^{s^2} - 1)e^{-\theta|u-v|}$; it ignores the smoothing of the modulation by the kernel, so it slightly overstates long-window variance. The daily result adds Proposition 1 to the long-window Hawkes limit. □

Flavours. Each sale's flavour is categorical: the week's limited flavour with probability 0.15 while on sale, otherwise plain or Red in the receipt-data ratio 53.3 : 14.8 [20].

Simulation. The server advances in $\Delta t = 100$ ms ticks. It recomputes the store rates λ_i at 15 s intervals and the weather at 10 min intervals; updates X with the exact transition $X \leftarrow Xe^{-\theta\Delta t} + s\sqrt{1 - e^{-2\theta\Delta t}}\,Z$; draws $n \sim \mathrm{Poisson}\big((1-\eta)\Lambda M \Delta t\big)$ immigrants, assigning each to a store by binary search on the cumulative rates in $O(\log n)$; releases due offspring from a min-heap; and schedules Poisson(η) children per sale. Gamma variates use Marsaglia–Tsang [25]. A two-minute warm-up starts the process close to its stationary regime, and viewers receive a shared stream.

6 Validation

We run the production code offline with seeded random numbers (`scripts/validate.mts`): eight hours at fixed lunch-time rates ($\Lambda = 23.52$ s^{-1}) against a plain Poisson process with identical rates, and one full neutral weekday. Table 3 summarises the results.

Mean preservation. The full simulated day lands within 0.1% of the anchor, as Proposition 2 predicts.

Overdispersion. Figure 4 compares the empirical Fano factor with (9). Poisson stays at 1; ours rises with the window as the Hawkes term saturates near $(1-\eta)^{-2} \approx 2.37$ and the slow modulation takes over. The approximation slightly overstates long-window variance, plausibly because it ignores kernel smoothing. The daily Pearson dispersion matches Proposition 3 to two decimals (8.72 vs. 8.71), and the store-day distribution (Figure 5) is considerably wider than a Poisson mixture with the same means, qualitatively consistent with the heterogeneity of store-level retail data [15].

Burstiness. Normalising each store's inter-purchase gaps by its own mean, Poisson gives $B \approx 0$ while our process gives $B = 0.18$: more very short gaps and a heavier tail (Figure 6), consistent with clustered activity. Figure 7 shows five minutes of national per-second counts.

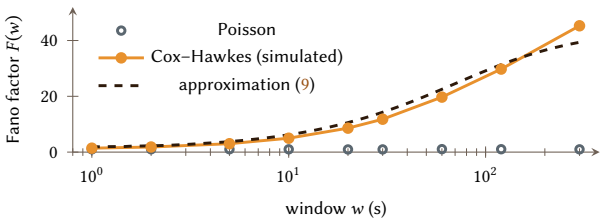


Figure 4. Variance-to-mean ratio of national counts by window length, at lunch-time rates.

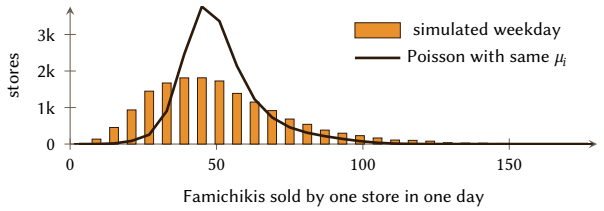


Figure 5. Daily store counts over one simulated weekday.

7 Parameters

Table 2 lists the parameters. The assumed values are chosen to be plausible and to reproduce the qualitative regularities in the literature (lunch peaks, cooler days selling more hot snacks, overdispersed and bursty counts); they are not fitted to FamilyMart sales data, which we could not obtain.

8 Limitations

Without access to store-level sales we cannot validate against observed data: the model is calibrated to published totals and documented regularities. Store types are inferred from names; attraction ignores catchment populations and other chains; weather slopes are assumed rather than estimated; and the intraday profiles are stylised. Several of these assumptions could be replaced by estimates given additional data (foot-traffic meshes, POS panels, prefecture-level convenience-store statistics). The live site labels its figures as estimates.

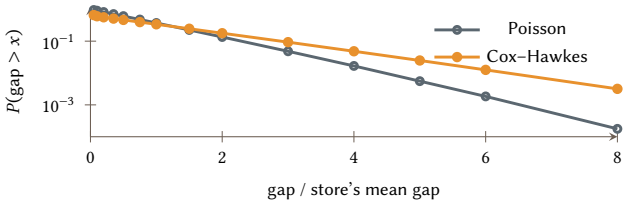


Figure 6. Tail of normalised inter-purchase gaps at individual stores.

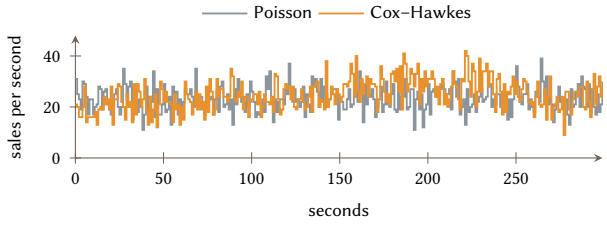


Figure 7. Five minutes of national sales per second at lunch, both at the same mean rate.

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