Disadoption Contagion in KFP: Operationalization, Models, and Results

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1 Introduction

This note formalizes "disadoption contagion" for the Korean Family Planning (KFP) data and outlines estimands and models that leverage the general time–by–state information encoded in `TOA_derivado_general`. The aim is to (i) clarify concepts and operational definitions for adoption vs. disadoption, (ii) collapse 21 detailed states to three meta-states when needed, (iii) propose regression designs—event–history for *stable* disadoption and panel/transition models for *temporary* disadoption—, and (iv) review the performance of those models once `7-disadoption-regression-final.R` was run.

1.1 Adoption vs. Disadoption in the classical framework

Classical diffusion treats adoption as a one–off, irreversible event per ego ("time of adoption", TOA). In real usage data, contraceptive behavior fluctuates: egos can move from a modern method to traditional/no use and later revert. Thus, while the *adoption* construct is convenient for event–history modeling, observed trajectories reveal multiple episodes of adopting and disadopting across time.

1.2 What is observed in `TOA_derivado_general`

With the period–by–ego status matrix (1047×11) and complete state labels (21 categories), heatmaps and random trajectories show frequent switching. This richer object validates the standard TOA reconstruction (so it is *consistent* with Valente's prior work, see Table 10-2 from Valente's 2010 book) while enabling analyses beyond a single adoption event: repeated adoptions, disadoptions, and state sojourns.

1.3 Data, states, and network

We observe an ego-by-period contraceptive-status panel (11 waves) with 21 original states collapsed to three meta-states:

$$\begin{aligned}
\mathsf{Modern} &= \{\text{Loop, Pill, Condom, Vasectomy, TL, Injection}\} \\
\mathsf{Traditional} &= \{\text{Rhythm, Withdrawal, etc.}\} \\
\mathsf{NoUse} &= \{\text{NormalB, Want More, No more, Pregnant, Infertile, Abortion, ...}\}.
\end{aligned}$$

Let $S_{it} \in \{\mathsf{Modern}, \mathsf{Traditional}, \mathsf{NoUse}\}$ and $M_{it} = \mathbf{1}\{S_{it} = \mathsf{Modern}\}$. Period-$t$ networks $A(t) = [A_{ij}(t)]$ are directed adjacency matrices among surveyed alters.

Sample actually used in the models: All models in this paper restrict the risk set to individuals who were *ever* modern method users ("ever-modern"). That is, egos must have used a modern method at least once during the observation window to be included.

1.4 Disadoption as recurrent events

Under this view, *disadoption* is any transition leaving Modern:

$$\mathsf{Modern} \to \mathsf{Traditional} \quad \text{or} \quad \mathsf{Modern} \to \mathsf{NoUse}.$$

These transitions can be *recurrent*: the same ego can disadopt, then re–adopt, multiple times.

2 Exposure to disadoption

Mirroring adoption exposure, I define disadoption exposure as the local prevalence of alters who have *left* modern use. Define cohesion exposure (lagged by one period) as the share of ego i's alters in Modern:

$$E_i(t) = \frac{\sum_j A_{ij}(t) M_{j,t-1}}{\sum_j A_{ij}(t)} \quad (\text{with } 0/0 := 0).$$

Track the within-ego running maximum $E_i^{\max}(t) = \max_{u \le t} E_i(u)$ and define the *disadoption gap*:

$$E_i^D(t) = E_i^{\max}(t) - E_i(t) \in [0, 1].$$

Intuition: when neighbors who had been modern stop being modern, $E_i(t)$ falls below its past peak and $E_i^D(t)$ rises.

2.1 Flow-style exposure (temporary churn)

To probe short-run "churn" away from Modern, we compute period-τ neighbor disadoption flow as

$$F_i(\tau) = \frac{\sum_j A_{ij}(\tau)\, \mathbf{1}\{M_{j,\tau-1} = 1,\ M_{j,\tau} = 0\}}{\sum_j A_{ij}(\tau)}.$$

We then form windowed sums $F_i^{(W)}(t) = \sum_{\tau=t-W+1}^{t} F_i(\tau)$ (with $t \ge 2$) and use the $t-1$ lag in regressions. Windows $W \in \{1, 2, 3, 4, 5, 6\}$ were evaluated.

2.2 Temporary vs. Stable disadoption

- **Temporary disadoption**: any period with $S_{it} \ne \mathsf{Modern}$ after being modern earlier, regardless of eventual return.
- **Stable disadoption**: the *last* exit from Modern followed by no return up to the observation horizon; formally, the terminal transition $\mathsf{Modern} \to \{\mathsf{Traditional}, \mathsf{NoUse}\}$ with no subsequent Modern.

2.3 Implications for modeling

- For **stable** disadoption, an event–history (survival / discrete–time hazard) design aligns with the single "terminal" event per ego.
- For **temporary** disadoption, a panel transition model (multinomial or binary flows per period) captures repeated moves with time–varying exposures.

3 The models

3.1 Stable disadoption model (final A-models)

Stable (terminal) disadoption is modeled as a discrete-time hazard with period effects and village fixed effects:

$$
\begin{aligned}
\text{logit}\ \Pr\{Y_{it} = 1 \mid \mathcal{F}_{t-1}\} = \alpha_t + \beta_D\, E_i^D(t) + \beta_E\, E_i(t) + \gamma_{\text{deg}}^\top \mathbf{d}_{it} + \delta\, \text{CumDisadopt}_{g(i)}(t) \\
+ \theta_1\, \text{children}_i + \theta_2\, \text{age}_i + \theta_3\, \text{ageAtMarriage}_i + \theta_4\, \text{spousalComm}_i + \eta_{g(i)},
\end{aligned}
$$

where $\mathbf{d}_{it} = (\text{deg}_{\text{in}}, \text{deg}_{\text{out}})$, η_g are village fixed effects, and controls match the implemented covariates in `R`:

Covariates used: `cumdis_g_lag`, `children`, `age_lag`, `agemar_lag`, `comop2_yes`.

Estimation is by logit with period dummies and village FE.

Identification notes. Period dummies absorb common shocks; village FE capture time-invariant village heterogeneity. Degrees and `E_adopt_lag` enter to benchmark against adoption-style cohesion. The correlation between `age_lag` and `agemar_lag` is low in our analytic panel, so both can be included without severe redundancy.

3.2 Temporary disadoption checks (B-models)

To test whether very recent neighbor exits predict ego disadoption beyond the stable design, we estimated windowed flow models with the same FE/covariate set:

$$
\text{logit}\ \Pr\{Y_{it} = 1 \mid \mathcal{F}_{t-1}\} = \alpha_t + \phi_W\, F_i^{(W)}(t-1) + \beta_E\, E_i(t) + \gamma_{\text{deg}}^\top \mathbf{d}_{it} + \delta\, \text{CumDisadopt}_{g(i)}(t) + \Theta^\top \mathbf{C}_i + \eta_{g(i)},
$$

for $W \in \{1, \ldots, 6\}$, $\mathbf{C}_i = \{\texttt{children}, \texttt{age}, \texttt{ageAtMarriage}, \texttt{spousalComm}\}$, and ϕ_W is the (window-specific) log-odds coefficient on the windowed flow exposure $F_i^{(W)}(t-1)$: it measures the multiplicative change in the odds of disadoption associated with a one-unit increase in recent neighbor exits aggregated over the last W transitions.

4 Key empirical results

All results correspond to the script `7-disadoption-regression-final.R`, which constructs E, $E^{\max}$, E^D, the windowed flows $F^{(W)}$, the at-risk panel, and estimates (A) and (B) models with village FE and the covariate set

{`cumdis_g_lag`, `children`, `age_lag`, `agemar_lag`, `comop2_yes`}.

4.1 Sample and general checks

- Panel rows = 1634; unique egos = 377; events = 377 (one terminal disadoption per ego).
- Degrees and `E_adopt_lag` are not robust predictors once FE and covariates are included.
- **Collinearity check**: `cor(age_lag, agemar_lag)` is low; both can be used jointly.

4.2 Stable disadoption (A-models)

- **Disadoption gap** E^D: consistently *protective* (OR<1) and statistically significant across A-models with FE. In a representative specification with age+age-at-marriage (A4), $\widehat{\mathrm{OR}}(E^D) \approx 0.35$ (about a 65% reduction in the odds per unit of the gap), controlling for E, degrees, period and village FE, and covariates.

- **Age**: positive association with disadoption odds (e.g., OR ≈ 1.09 per year), statistically significant and stable across models that include it.

- **Age at marriage**: negative association (protective), statistically significant in most specifications (e.g., OR $\approx$ 0.93–0.94 per year).

- **Spousal communication (comop2)**: point estimate <1 (protective direction) but not statistically significant when entered additively with FE.

- **Model comparison**: among (A) models, those with age and age-at-marriage (A4) or with the full set (A7) achieved the best AIC while preserving the E^D effect.

  See **Appendix A** to see the result for the A4 model.

4.3 Temporary/flow-style (B-models)

- We estimated VFE models for $W = 1, \ldots, 6$ using $F_i^{(W)}(t-1)$. Effects are not robustly significant across windows.

- Signs tend to be positive (OR$>$1) for very short windows and turn negative (OR$<$1) for longer windows, suggesting that *accumulated* neighbor exits may correlate with lower ego disadoption once we condition on village/time FE and covariates.

- The **best** window by AIC and p among B-models is $W = 5$, where $\widehat{\phi}_{W=5} < 0$ (e.g., $\beta \approx -0.55$, OR≈ 0.58) with $p \approx 0.10$ when controlling for `agemar_lag` and `comop2_yes`. This is borderline and not conventionally significant; overall, B-models compare unfavorably to the stable (A) models in both fit and significance.

5 Interpretation

Stable disadoption (A): The *gap* exposure E^D appears to capture a meaningful social anchoring: when an ego's current cohesion to modern users falls below her past peak, the odds of terminal disadoption *decrease* after adjusting for village/time effects and individual covariates. Age raises risk; age at marriage reduces it; spousal communication is directionally protective but small and imprecise.

Temporary/flow-style (B): Windowed short-run churn in neighbors' exits does not provide consistent additional signal once we include FE and covariates. Empirically, the evidence is weak compared with the stable-gap story.

Only E^D is robustly significant, and its sign runs *counter* to imitation: In classic contagion narratives, more neighbors leaving would raise one's own hazard via *imitation*. Here, the significant predictor is the *gap* E^D, and its coefficient is *protective* (OR<1): larger past-peak minus current exposure is associated with *lower* odds of terminal disadoption.

Link to general disadoption theory: In the broader literature, disadoption has been described as a form of long-term cessation rather than a simple switch or temporary pause (Lehmann 2017). Additionally, one might expect a process of imitation: if many neighbors leave, the social signal would encourage others to leave as well. Our findings suggest the opposite. A larger disadoption gap is associated with a lower likelihood of terminal disadoption, hinting at a kind of counter–reaction dynamic. Rather than following neighbors out of modern use, egos appear more anchored in their own modern practice when surrounded by exits, moving the story away from classic contagion by imitation.

6 Appendix A: Exact R console output for summary(A4)

The A4 model is a discrete–time logistic hazard model of *stable disadoption*. It includes period dummies and village fixed effects, with the following covariates:

- $E_i^D(t)$ (`E_gap_lag`): disadoption gap, measuring the fall from maximum to current adoption exposure.
- $E_i(t)$ (`E_adopt_lag`): cohesion exposure to current modern users.
- $\mathrm{deg}_{\mathrm{in}}, \mathrm{deg}_{\mathrm{out}}$: in– and out–degree.
- `cumdis_g_lag`: cumulative village disadoptions up to $t-1$.
- `children`: number of children (sons+daughters).
- `age_lag`: respondent's age.
- `agemar_lag`: age at marriage.

All individuals in the analytic sample are *ever–modern users* (egos who adopted a modern method at least once).

6.1 Exact R console output

```
==============================
= A4: GAP+VFE + age + agemar =
==============================


Call:
glm(formula = fm, family = fam, data = panel)

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)   -3.641281   1.003529  -3.628 0.000285 ***
E_gap_lag     -1.058103   0.456102  -2.320 0.020347 *
E_adopt_lag   -0.325873   0.439427  -0.742 0.458339
deg_in_lag    -0.003795   0.018868  -0.201 0.840616
deg_out_lag    0.005901   0.029252   0.202 0.840133
per3           1.212251   0.245249   4.943 7.70e-07 ***
per4           1.941646   0.294659   6.589 4.41e-11 ***
per5           2.747366   0.369534   7.435 1.05e-13 ***
```

```
per6           3.214080   0.453747   7.083 1.41e-12 ***
per7           3.914044   0.530932   7.372 1.68e-13 ***
per8           4.315527   0.604046   7.144 9.04e-13 ***
per9           5.189193   0.698303   7.431 1.08e-13 ***
per10          6.117358   0.854876   7.156 8.32e-13 ***
per11         20.392136 298.340652   0.068 0.945506
cumdis_g_lag  -0.118522   0.037188  -3.187 0.001437 **
children      -0.279863   0.066249  -4.224 2.40e-05 ***
factor(g)2    -0.018478   0.412379  -0.045 0.964259
factor(g)3     0.799971   0.442948   1.806 0.070916 .
factor(g)4    -0.297267   0.466778  -0.637 0.524224
factor(g)5     0.340705   0.382215   0.891 0.372718
factor(g)6     0.753055   0.424093   1.776 0.075785 .
factor(g)7     0.711506   0.387457   1.836 0.066306 .
factor(g)8     0.187783   0.425428   0.441 0.658925
factor(g)9     0.263105   0.433517   0.607 0.543912
factor(g)10   -0.334373   0.407217  -0.821 0.411580
factor(g)11   -0.140679   0.407156  -0.346 0.729707
factor(g)12   -0.470493   0.487044  -0.966 0.334035
factor(g)13    1.121937   0.417605   2.687 0.007218 **
factor(g)14    0.255691   0.494615   0.517 0.605192
factor(g)15    0.298841   0.458084   0.652 0.514162
factor(g)16    0.743202   0.439326   1.692 0.090706 .
factor(g)17    0.791411   0.431194   1.835 0.066447 .
factor(g)18    0.789494   0.469992   1.680 0.092996 .
factor(g)19    0.757660   0.478181   1.584 0.113088
factor(g)20    1.515179   0.529428   2.862 0.004211 **
factor(g)21    0.465289   0.474921   0.980 0.327225
factor(g)22   -0.504256   0.600700  -0.839 0.401218
factor(g)23    0.382425   0.497825   0.768 0.442374
factor(g)24    1.512170   0.519880   2.909 0.003629 **
factor(g)25   -0.948140   0.644196  -1.472 0.141069
age_lag        0.089129   0.018410   4.841 1.29e-06 ***
agemar_lag    -0.054971   0.030601  -1.796 0.072439 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1765.2  on 1633  degrees of freedom
Residual deviance: 1533.7  on 1592  degrees of freedom
AIC: 1617.7

Number of Fisher Scoring iterations: 13
```

6.2 Interpretation of A4 coefficients

- (E^D, `E_gap_lag`): $\hat{\beta} = -1.06 \Rightarrow \text{OR} = \exp(-1.06) \approx 0.35$.

Each unit increase in the gap is associated with a **65% reduction** in the odds of stable disadoption.

- (E, `E_adopt_lag`): $\hat{\beta} = -0.33 \Rightarrow \text{OR} \approx 0.72$.

  This effect is not statistically significant, but directionally suggests that higher contemporaneous exposure to modern users reduces disadoption risk.

- (`children`): $\hat{\beta} = -0.28 \Rightarrow \text{OR} \approx 0.76$.

  Each additional child decreases the odds of disadoption by about **24%**, statistically significant.

- (`age_lag`): $\hat{\beta} = 0.089 \Rightarrow \text{OR} = \exp(0.089) \approx 1.09$.

  Each additional year of age increases the odds of disadoption by about **9%**, statistically significant.

- (`agemar_lag`): $\hat{\beta} = -0.055 \Rightarrow \text{OR} \approx 0.95$.

  Each additional year of age at marriage reduces the odds of disadoption by about **5%**, marginally significant.