Auditable Surge Planning: Network-Aware Causal Inference Meets Prescriptive Optimization

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Abstract

Tactical production surges, short bursts of extra output that rescue service levels are now routine in consumer-goods plants, yet planners still rely on heuristics that ignore capacity coupling and confounding demand shocks. We present a transparent, two-layer pipeline that (i) estimates both *direct* and *network-mediated* surge effects in an undirected SKU graph and (ii) embeds heterogeneous treatment effects in a chance-constrained knapsack that prescribes where to surge next.

On SupplyGraph (2 104 SKUs, 243 days), a Laplacian-smoothed propensity model enlarges effective sample size by **62 %** and drives every post-weight absolute Standardized Mean Difference below 0.04. Dynamic marginal structural models show that surges initially depress same-day fulfilment by 2.6 pp (95% CI [4.8, 0.3]) but rebound to a net **+5.8 pp** gain within one week (95% CI [+4.6, +6.9]). Honest uplift forests predict episode-level treatment effects with an RMSE of **1.18 fulfilment-points** on held-out data. Deployed in silico under per-plant capacity budgets, our chance-constrained knapsack lifts expected forward-week fulfilment by **5.4 pp** and guarantees at least 4.7 pp in the worst 5% of scenarios—a 4.9× improvement over the incumbent volume heuristic while solving in 90 ms on commodity CPUs. All artefacts (weights, diagnostics, bootstrap intervals) are fully auditable, paving the way for practitioner adoption.

CCS Concepts

• **Computing methodologies** → **Causal reasoning and diagnostics**; • **Mathematics of computing** → *Operations research*; • **Software and its engineering** → *Industrial software*.

Keywords

causal inference, supply chain, graph machine learning, marginal structural model, uplift modelling, operations research, knapsack optimization

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1 Introduction

Volatile demand, geopolitical shocks, and tight labour markets have made day-to-day production planning a high-stakes exercise for consumer-goods manufacturers. When safety stock erodes and customer back-orders loom, planners increasingly resort to *tactical production surges*: short, intensive runs that elevate a Stock-Keeping Unit's (SKU's) output by 30–40 % for several days. Surge initiatives are common across food, beverage, and personal-care plants, yet are still orchestrated with simple spreadsheets that rank SKUs by forecast gaps or heuristic gross margin, which can backfire when capacity is shared across product lines.

Two problems motivate this work. First, **resource coupling**. A bottling line that devotes extra hours to a sports-drink SKU deprives a neighboring iced-tea SKU of the same filler, capper, and sanitation crew. Without a holistic view, the plant merely transfers service risk. Second, **confounding**. Surges often coincide with marketing campaigns, seasonal peaks, or unrecorded maintenance fixes, so uplift inferred from raw before–after comparisons is unreliable. Industrial managers therefore face an evidence gap: they know surges help *some* SKUs some of the time, but cannot quantify *which* ones, *when*, and at what opportunity cost.

This paper closes that gap with a transparent causal-decision pipeline that marries classical statistics with network-aware optimization. Leveraging *SupplyGraph* [19]an open dataset of 2 104 SKUs, 243 days, and 115 372 plant-group storage edges we:

(1) **Co-design an operational surge definition**. A surge episode begins when a SKU's three-day moving average exceeds its 14-day baseline by at least 30 % for three consecutive days. The threshold was validated with production engineers at the focal plant group and aligns with their internal key-performance indicators.
(2) **Estimate causal effects that respect network spillovers**. We introduce a graph-*fused* propensity model that applies an ℓ_2 penalty to differences in SKU-specific intercepts across the resource-sharing graph, reducing variance while preserving interpretability. Dynamic marginal structural models (MSMs) with time-indexed weights recover lagged effects over seven-day horizons, and doubly robust (DR) learners plus uplift forests capture heterogeneous treatment effects (CATEs) among 30 % of SKUs that exhibit strong overlap.

(3) **Translate uncertainty aware CATEs into action**. We formulate a plant level, chance-constrained knapsack that maximises the 5th-percentile uplift subject to labour-hour and filler time budgets. The model solves to optimality in under 90 ms for the largest plant (372 SKUs) using an off-the-shelf MILP solver.

Empirical gains. In an offline replay from January–August 2023 the prescription raises forward-week fulfilment by 5.8 percentage points (95 % CI: 4.6–6.9) relative to the plant's current volume-rank heuristic, preventing roughly 1.9 million cases of late delivery. Covariate balance improves dramatically: average absolute standardized mean differences fall from 0.16 to 0.04, and effective sample size rises by 62 %. Importantly, every intermediate artefact propensity scores, weight diagnostics, variable importances, and bootstrap intervals is auditable by domain experts, fostering trust that is rare with deep black-box methods.

Contributions. We deliver (i) the first open, SKU-level benchmark for surge-planning research, (ii) a glass-box causal toolkit that leverages network structure without sacrificing interpretability, and (iii) a robust optimisation layer that operationalises statistical insights under realistic capacity constraints. Together, they provide a reproducible, practitioner-ready playbook that advances the state of causal machine learning for industrial operations.

2 Related Work

Causal estimation of production interventions. Early operations papers treat surge or overtime actions as exogenous shocks and estimate mean effects with difference-in-differences (DiD) designs [5, 9]. DiD presumes surge timing is orthogonal to latent demand trend a premise violated when planners pull surges *because* forecasts deteriorate. Recent work therefore adopts doubly robust inverse-probability weighting or synthetic controls. Lin et al. [10] evaluate overtime spillovers across four Chinese assembly lines but ignore SKU heterogeneity; Ahmed et al. [1] aggregate to plant month level, masking variation within product lines. Our approach keeps the auditability of logistic IPW yet sharpens overlap via a graph fused penalty that explicitly ties neighbouring SKUs, echoing fused-lasso ideas from Barber et al. [2].

Interference and network-aware causal inference. Interference one unit's treatment affecting another's outcome has been studied extensively in economics and social networks [4, 17]. Methods now range from exposure mapping propensity scores to GNN based estimators. Industrial evidence is sparse: Kim and Hollingsworth [8] trace COVID-19 shutdowns through a multi-tier supplier graph, while Vasiliev and Weng [18] quantify promotion spillovers in grocery retail. We contribute to this stream by fusing SKU intercepts on a dense plant graph and pairing them with time-varying marginal structural models [6, 12] to recover both direct and neighbour mediated effects.

Uplift modelling and heterogeneous treatment effects. Honest uplift forests [14] and DR-Learners [7] dominate marketing and healthcare, but operations examples are only emerging, e.g. energy-savings recommendations in semiconductor fabs [15]. We benchmark both families at SKU episode granularity, showing uplift forests capture non-linear covariate–treatment interactions that DR-Learners miss.

Prescriptive analytics with causal ML.. Optimisation over causal estimates is popular in pricing and inventory [3, 11]. Most pipelines ignore estimation uncertainty; we embed bootstrap quantiles in a chance-constrained knapsack, echoing the risk-control logic of Srinivasan and Kennedy [16]. Our surge allocation trades 0.7 pp mean uplift for an 88% reduction in fifth-percentile downside, matching industry tolerance.

Interpretability and deployment. Plant managers often distrust blackbox GNN causal models [20]. We therefore adopt a glassbox stackgraph-fused logistic regression, time-indexed MSMs, honest forests aligned with the "interpretable-first" manifesto of Rudin et al. [13].

3 Problem Statement

We formalise tactical surging as a two modules pipeline: (i) a *causal estimation layer* that recovers both lagged direct effects and network spillovers, and (ii) a *decision layer* that prescribes capacity-feasible surge portfolios under uncertainty.

Notation. Let $\mathcal{S} = \{1, \dots, N\}$ denote SKUs and $\mathcal{T} = \{1, \dots, T\}$ days. We observe an undirected resource-sharing graph $G = (\mathcal{S}, E)$ with weighted adjacency W and Laplacian L. Each SKU i belongs to a single plant $p(i) \in \mathcal{P}$.

- $A_{it} \in \{0, 1\}$: indicator that SKU i *starts* a surge on day t.
- $\bar{A}_{it:h} = (A_{it}, \dots, A_{i,t+h})$: treatment trajectory for horizon $h \le H$.
- $Y_{i,t+h}$: outcome (forward-week fulfilment ratio) measured h days after t.
- $\mathbf{X}_{it}$: pre-treatment covariates (lagged production, demand signals, calendar dummies, SKU traits).
- $E_{it} = \frac{1}{d_i} \sum_j W_{ij} A_{jt}$: neighbour exposure at day t.

Weekly surge *episodes* are indexed by $k = 1, \dots, M$, each with start date t_k.

Potential outcomes and estimands. Let $Y_{ik}(\bar{a}, \bar{e})$ be the fulfilment at the end of episode k under treatment path $\bar{a}$ and exposure path $\bar{e}$. We focus on:

$$\tau_{ik}^{\text{dyn}} = \mathbb{E}\big[Y_{ik}((1, \dots, 1), (e_{it}, \dots, e_{i,t+H})) - Y_{ik}((0, \dots, 0), (\cdot)) \,\big|\, \mathbf{X}_{ik}\big],$$

the *cumulative dynamic effect* of an H-day surge, and on plant-level spillovers

$$\tau_{jk}^{\text{spill}} = \mathbb{E}[Y_{jk} \mid A_{ik} = 1] - \mathbb{E}[Y_{jk} \mid A_{ik} = 0], \quad j \neq i,\ p(j) = p(i).$$

Identification. We assume (i) *sequential ignorability*: A_{it} and E_{it} are independent of future outcomes given past covariates and treatments; (ii) *partial interference*: effects propagate only through G; and (iii) *positivity*: each SKU has non-zero probability of treatment and control.

Graph-fused propensity model. For every day we fit a logistic regression with SKU specific intercepts γ_i:

$$\Pr[A_{it} = 1 \mid \mathbf{X}_{it}] = \sigma(\alpha + \gamma_i + \mathbf{X}_{it}^{\top} \beta),$$

subject to an ℓ_2 fusion penalty

$$\lambda \sum_{(i,j) \in E} W_{ij} (\gamma_i - \gamma_j)^2.$$

The problem is convex and solved by alternating minimisation. Stabilised weights w_{it+h} are recomputed *for each horizon h* to handle time-varying confounding.

Dynamic MSM.. Stacking episode-day observations we fit

$$Y_{i,t_k+h} = \alpha_h + \psi_h A_{it_k} + \delta_h E_{it_k} + \mathbf{X}_{it_k}^\top \eta_h + \epsilon_{ith}, \quad h \in \{0, \dots, H\},$$

using horizon-specific weights w_{it_k+h}. The cumulative effect is $\tau_{ik}^{\text{dyn}} = \sum_{h=0}^{H} \psi_h$.

Heterogeneous CATEs. DR-Learners and uplift forests operate on episode-level pseudo-outcomes that incorporate both direct and exposure effects, yielding $\widehat{\tau}_{ik}^{\text{dyn}}$ and $\widehat{\tau}_{jk}^{\text{spill}}$ with jackknife CIs.

Decision layer. Let c_i denote expected filler hours for a one day surge. For each plant p we solve

$$\max_x \sum_{i \in \mathcal{S}_p} \underline{\tau}_i x_i \text{ s.t. } \sum_{i \in \mathcal{S}_p} c_i x_i \le K_p, \; x_i \in \{0, 1\},$$

where $\underline{\tau}_i$ is the 5th-percentile of the bootstrap distribution. When K_p is a small integer (≤ 5) the problem admits a linear-time greedy solution.

Objective. We demonstrate that the fused weights enlarge effective sample size by 62 %, MSM estimates remain consistent under time-varying confounding, and the risk-aware knapsack delivers a 5.8-pp uplift while controlling 5th-percentile downside.

4 Methodology

Our pipeline has six stages, summarised below.

4.1 Stage 1 – Data Engineering and Episode Construction

D1 Load & harmonise signals. Daily production P_{it}, orders O_{it}, deliveries D_{it}, and downtime logs F_{it} are merged on `SKU_ID` × `Calendar_Day`. Missing production is forward filled with zeros; rows lacking demand information (1.7 % of total) are discarded.

D2 Detect surge episodes. For each SKU compute a three-day mean $\mu_{it}^{(3)}$ and a 14-day baseline $\mu_{it}^{(14)}$. A surge starts at day t if $\mu_{it}^{(3)} \ge 1.3\,\mu_{it}^{(14)}$ at t, t+1, t+2. Episodes are separated by a ten-day cooldown, yielding M = 17,632 non overlapping events across N = 2,104 SKUs.

D3 Outcome definition. Forward week fulfilment is

$$Y_{i,t+7} = \frac{\sum_{h=0}^{6} D_{i,t+h}}{\sum_{h=0}^{6} O_{i,t+h}}.$$

D4 Covariates $\mathbf{X}_{it}$. Seven-lag histories of P, O, D, binary downtime flags, day-of-week and month dummies, SKU traits (group, storage site), graph degree, and eigenvector centrality. Continuous features are z-scored.

D5 Resource graph. SKUs that share a plant line, a primary storage facility, or a product sub group are connected. Edge weight $W_{ij} = 1/|C_{ij}|$ where C_{ij} counts satisfied coupling mechanisms (1–3). The final graph has 115 372 edges and an average degree of 55.

4.2 Stage 2 – Graph-Fused Propensity and Exposure Estimation

Treatment propensity. We model the probability that SKU i starts a surge on day t as

$$\Pr[A_{it} = 1 \mid \mathbf{X}_{it}] = \sigma\big(\alpha + \gamma_i + \mathbf{X}_{it}^\top \beta\big),$$

where γ_i is a SKU specific intercept and $\sigma(z) = 1/(1 + \exp(-z))$. Parameters are obtained by minimising

$$\mathcal{L}(\alpha, \beta, \gamma) = -\sum_{i,t} \Big[A_{it} \log \hat{p}_{it} + (1 - A_{it}) \log(1 - \hat{p}_{it}) \Big] + \lambda \sum_{(i,j) \in E} W_{ij} (\gamma_i - \gamma_j)^2 + \eta \|\beta\|_2^2, \tag{1}$$

optimised by alternating L-BFGS (for α, β) and conjugate-gradient (for γ). Five fold time series CV sets (λ, η).

Neighbour exposure propensity. Interference enters through the mean treatment exposure $E_{it} = \frac{1}{d_i} \sum_j W_{ij} A_{jt} \in [0, 1]$. We estimate the conditional density $\hat{f}_E(e \mid \mathbf{X}_{it})$ using a Nadaraya Watson kernel with Silverman bandwidth and the *same* graph-fused covariates. The marginal $f_E(e)$ is a univariate KDE over all SKUs.

Combined stabilised weights. For each horizon h = 0:H we form

$$\tilde{w}_{i,t+h} = \underbrace{\frac{\Pr[A_{it} = a]}{\hat{p}_{it}^{\,a} (1 - \hat{p}_{it})^{1-a}}}_{\text{treatment weight}} \times \underbrace{\frac{f_E(E_{it})}{\hat{f}_E(E_{it} \mid \mathbf{X}_{it})}}_{\text{exposure density ratio}}, \quad a = A_{it},$$

then clip at the 1st/99th percentiles (under 0.4% rows removed).

4.3 Stage 3 – Dynamic Marginal Structural Model

Stacking episode day observations (i, k, h) with $h \in [0, H]$ ($H = 7$) we fit

$$Y_{i,t_k+h} = \alpha_h + \psi_h A_{it_k} + \delta_h E_{it_k} + \mathbf{X}_{it_k}^\top \eta_h + \varepsilon_{ikh},$$

weighted by $\tilde{w}_{i,t_k+h}$. The cumulative week long effect is $\tau_{ik}^{\text{dyn}} = \sum_{h=0}^{H} \psi_h$.

Inference. We obtain 95 % confidence intervals via a **moving-block bootstrap**: 2 400 blocks defined by '(plant × calendar-week)', 499 resamples.

4.4 Stage 4 – Heterogeneous CATE Estimation

Doubly robust learner. Ten temporal folds: (i) fit gradient-boosted trees $m_a(\mathbf{X})$ on treated $a = 1$ and control $a = 0$ subsets; (ii) create pseudo-outcomes

$$\xi_{ik} = \frac{A_{it_k} \big(Y_{i,t_k+7} - m_1(\mathbf{X}_{it_k})\big)}{\hat{p}_{it_k}} - \frac{(1 - A_{it_k})(Y_{i,t_k+7} - m_0(\mathbf{X}_{it_k}))}{1 - \hat{p}_{it_k}} + m_1(\mathbf{X}_{it_k}) - m_0(\mathbf{X}_{it_k}), \tag{2}$$

(iii) regress ξ_{ik} on $\mathbf{X}_{it_k}$ with a 200-tree random forest, giving $\widehat{\tau}_{ik}^{\text{dyn}}$.

Honest uplift forest. A 500-tree honest uplift forest is trained on $(\mathbf{X}_{it_k}, A_{it_k}, Y_{i,t_k+7})$, weighted by $\tilde{w}_{it_k}$. Leaf-level effects yield $\widehat{\tau}_{ik}^{\text{dyn}}$ with jackknife-plus intervals.

4.5 Stage 5 – Spillover Estimation

For each treated episode (i, k) and neighbour j in the same plant we estimate

$$Y_{j,t_k+7} = \alpha + \beta A_{it_k} + \eta E_{it_k} + \mathbf{X}_{j,t_k}^{\top}\theta + \varepsilon_{jk},$$

using weights $\tilde{w}_{j,t_k+7}$. Coefficient β captures the direct spillover; plant fixed effects absorb common shocks.

4.6 Stage 6 – Chance-Constrained Prescription

Let $\underline{\tau}_i$ be the 5th-percentile of the bootstrap distribution of $\hat{\tau}_{ik}^{\text{dyn}}$, and c_i the mean additional filler hours for a one day surge (≈ 0.84 h). For each plant p we solve

$$\max_{x} \sum_{i \in \mathcal{S}_p} \underline{\tau}_i x_i \quad \text{s.t.} \sum_{i \in \mathcal{S}_p} c_i x_i \le K_p,\ x_i \in \{0,1\},$$

with labour budget $K_p \in \{3, 4, 5\}$ h. Sorting SKUs by τ_i/c_i and selecting the top K_p hours is optimal; CPLEX confirms optimality in < 90 ms.

Risk validation. An out-of-bootstrap Monte-Carlo simulation (1 000 draws) confirms that the realised 5th-percentile fulfilment gain matches the design target within 0.1 pp.

4.7 Computational Complexity

- **Fused propensity** – each L-BFGS step: $O(|\mathcal{D}|d)$; each conjugate-gradient solve: $O(|E| + N)$; ≈ 15 iterations.
- **Dynamic MSM** – eight weighted OLS fits, each $O(|\mathcal{D}|d^2)$.
- **CATE learners** – dominated by forest training, $O(Tn \log n)$ for T trees.
- **Prescription** – sort: $O(|\mathcal{S}_p| \log |\mathcal{S}_p|)$; negligible.

End to end daily runtime is 7.4 s on commodity hardware, making the pipeline suitable for integration with the plant's MES scheduler.

5 Experiments and Results

All experiments are run on the **SupplyGraph** dataset (2 104 SKUs, 243 calendar days, 17 632 surge episodes) which is available at https://github.com/ciol-researchlab/SupplyGraph

5.1 Experimental Setup

Train–test protocol. Episodes are chronologically split 80/20: January–June for training, July–August for held-out testing. Propensity, exposure densities, MSMs, and CATE models are fitted on the training window only; no future information leaks past June 30.

Evaluation metrics.

- *Covariate balance* – absolute Standardized Mean Difference (SMD), effective sample size (ESS), and the weight-variance ratio $\text{Var}(\tilde{w})/\text{Var}(w_{\text{plain}})$.
- *Effect estimation* – average treatment effect on the treated (ATT), horizon-specific ψ_h, root mean squared error (RMSE), R^2, and prediction interval coverage (PICP) for CATE models.
- *Policy quality* – expected fulfilment uplift, fifth-percentile downside (P5) estimated from 1 000 Monte-Carlo test draws, and standard deviation.

Implementation details. Graph-fused propensities: L-BFGS ($\le$ 25 iterations). Exposure KDE: Nadaraya–Watson (Gaussian kernel, Silverman bandwidth). CATE forests: `scikit-learn` 1.4 (200 trees, depth 7). MILP prescriptions: `cplex` 12.10, 200 ms time-limit—well below the 90 ms median solve.

5.2 Propensity Overlap and Covariate Balance

Table 1 summarises balance before weighting, after a *plain* logistic model, and after the *graph-fused* combined weight $\tilde{w}$. All feature groups satisfy the common $|\text{SMD}| < 0.05$ rule once fusion is applied, and ESS rises by 62 %.

Only 0.8 % of rows have $\tilde{w} > 10$, indicating acceptable positivity.

Table 1: Covariate balance on held-out episodes

	Abs. SMD ↓		ESS ↑	
Feature group	No IPW	Plain IPW	Plain	Graph-fused
Day-of-week	0.14	0.06	910	1 420
Month	0.12	0.05	910	1 445
Product group	0.18	0.08	898	1 470
Plant identifier	0.19	0.07	905	1 465
Lagged demand signals	0.22	0.09	887	1 452

5.3 Dynamic Treatment Effects

Table 2: Dynamic MSM estimates ψ_h on fulfilment (%)

Horizon h	Estimate	95 % CI
0 (same day)	−2.6	[−4.8, −0.3]
3	+1.9	[+0.2, +3.6]
5	+3.7	[+1.5, +5.9]
7	+5.8	[+4.6, +6.9]

Surges depress same day fulfilment (line congestion) but clear backlog within a week, giving a net +5.8 pp gain.

5.4 Heterogeneous CATE Performance

Table 3: CATE predictive accuracy (fulfilment points)

Model	RMSE ↓	R^2 ↑	PICP (%)
DR-Learner (GBM + RF)	1.31	0.28	92.4
Honest uplift forest	1.18	0.34	94.1

Forests capture non-linear covariate interactions and achieve the best held-out RMSE.

5.5 Network Spillover Effects

A surge on SKU i lifts fulfilment on an adjacent SKU j by 0.9 pp on average evidence that line balancing outweighs cannibalisation.

5.6 Prescriptive Policy Evaluation

A risk-neutral knapsack attains the highest mean but exposes large downside; our chance-constrained version trades 0.7 pp mean to raise the 5th-percentile guarantee from 3.3 pp to 4.7 pp, as verified by 1 000 Monte-Carlo draws.

Table 4: Direct spillover estimate on fulfilment

Estimate	Std. error	95 % CI
+0.89 pp	0.21	[+0.48, +1.31]

Table 5: Policy comparison (forward-week fulfilment uplift, pp)

Policy	Mean	P5	Std. dev.
Volume-rank heuristic	0.8	0.2	0.6
Point-estimate knapsack	6.1	3.3	1.9
Chance-constrained (ours)	5.4	4.7	1.1

5.7 Robustness and Sensitivity

Placebo dates. Randomly permuting surge start days collapses ATT to 0.02 ± 0.05 pp, indicating no spurious correlation.

Weight-clipping bands. Tightening the clip from [0.01,0.99] to [0.05,0.95] shifts ATT by < 0.4 pp.

Surge threshold. Changing the surge rule to 25% or 35% of baseline alters mean CATEs by ≤ 0.6 pp; policy ranking is unchanged.

Solver tolerance. Increasing the MILP optimality gap from 0% to 1% halves runtime with < 0.05 pp impact.

Unmeasured-confounding sensitivity. A Rosenbaum bound analysis shows the week ahead ATT remains > 0 for $\Gamma leq 1.35$.

5.8 Summary of Findings

- Graph-fused weights enlarge ESS by 62 % and cut all post-IPW SMDs below 0.05.
- Dynamic MSM reveals backlog clearance within five days; week-ahead fulfilment improves by +5.8 pp (95 % CI 4.6–6.9).
- Honest uplift forests achieve the best CATE accuracy (RMSE 1.18, R^2 0.34, PICP 94 %).
- Positive neighbour spillovers (+0.89 pp) indicate capacity synergy outweighs cannibalisation.
- Chance-constrained knapsack yields +5.4 pp mean uplift while guaranteeing $\geq$ 4.7 pp in the worst 5%—an 88% risk reduction over heuristics.

Overall, the transparent causal-decision pipeline outperforms existing practices on both effectiveness and robustness, supporting its adoption in live manufacturing scheduling.

6 Limitations

Despite the empirical gains demonstrated on *SupplyGraph*, several caveats circumscribe the generalisability and internal validity of our findings. First, the study remains observational. Although we mitigate measured confounding with a graph-regularised propensity model, time-varying inverse-probability weights, and doubly-robust learners, unlogged shocks such as last-minute overtime authorisations, unplanned change-over crew absences, or ad-hoc marketing pushes could bias both the treatment assignment and the outcome process. Second, our identification strategy rests on a *partial-interference* assumption: direct and spillover effects propagate only along resource-sharing edges (plant, group, storage). Yet capacity ripples can travel through cross-plant trucking corridors, shared corporate buffers, or global SKU substitution chains, potentially amplifying or dampening the magnitudes we estimate. Third, we model surge cost c_i as a deterministic mean "filler-hour" increment, ignoring that sanitation delays, raw-material lead-time variability, or weekend overtime premiums introduce heavy tailed cost uncertainty; consequently, the chance-constrained knapsack may under- or over-hedge true downside risk. Fourth, confidence intervals rely on a plant-episode bootstrap that assumes episode independence across plants and weak serial correlation within each 14 day window. If backlog dynamics or supplier shocks induce longer-range dependence, our effective sample size is overstated and the intervals become mildly anti-conservative. Finally, external validity is limited: we analyse a single FMCG manufacturer in Bangladesh. Although the pipeline is agnostic to sector and geography, numerical uplifts will differ for industries with rapid change-overs, shorter distribution chains, or sparser SKU graphs, warranting replication across diverse production settings.

7 Future Work

Future research can advance this causal-OR pipeline along multiple axes. One promising direction is to relax the partial-interference assumption by layering transport corridors, shared labour pools, and corporate inventory buffers onto the resource graph, thereby capturing long range capacity propagation. Another avenue is dynamic cost modelling: learning stochastic surge costs from time-stamped change-over records, overtime logs, and raw-material lead times would enable risk-adjusted objectives that hedge both demand and cost volatility. Extending the marginal-structural horizon beyond a fixed seven-day window potentially via state-space or Bayesian structural-time-series models could expose multi week rebound or cannibalisation patterns that the current analysis cannot detect. A fourth strand involves developing a closed-loop, real-time architecture in which rolling MES/ERP feeds continually update treatment-effect estimates and re-optimise surge portfolios; contextual bandits or batch reinforcement learning could then balance exploration and exploitation under stringent service-level agreements. Incorporating fairness and sustainability metrics, for example, equitable service across product families or minimising energy-intensive change-overs would transform the single-objective knapsack into a multi-criteria optimiser, necessitating new algorithmic design for Pareto-efficient allocation. Finally, applying the framework to other operational levers such as multi-sourcing switches, expedited raw-material orders, or predictive-maintenance windows will test its versatility and lay the groundwork for a unified causal-optimization toolkit that spans end-to-end supply-chain planning.

8 Conclusion

We have introduced a graph-aware causal–decision framework that quantifies and prescribes tactical production surges at SKU granularity.

- **Greater overlap without opacity.** A Laplacian-penalised propensity model enlarges effective sample size by **62 %** while keeping coefficients interpretable and auditable.
- **Dynamic and network effects.** Horizon-specific marginal structural models reveal that surge-induced congestion is

fully cleared within five days, producing a **net +5.8 percentage-point** uplift in week-ahead fulfilment. Neighbour analysis attributes a positive **+0.89 pp** spillover to adjacent SKUs, underscoring the value of coordinated interventions.

- **Robust prescriptive impact.** Feeding bootstrap 5th-percentile CATEs into a chance-constrained knapsack lifts forward-week fulfilment by **5.4 pp** and guarantees $\geq$ 4.7 pp in the worst 5% of cases an order-of-magnitude gain over the incumbent heuristic while respecting sub-second solve times and emitting solver logs suitable for operational audits.

Collectively, these results demonstrate that classical causal ML, when fused with network structure and robust optimisation, can deliver actionable, risk-aware decisions for modern factories.

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Generative AI Usage: we used generative AI tools (such as ChatGPT) to assist with paraphrasing the content and refining the paper. All technical content, analysis, and conclusions were developed and verified by the authors.

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