Equilibrium Compliance under Transitory Visibility

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Abstract

This paper studies how compliance with non-market inputs with positive externalities responds to temporary, highly visible policy interventions in low-capacity environments. I develop a framework in which visibility operates as a coordination device: it raises contemporaneous compliance by increasing the observability of others' behaviour, while post-intervention persistence depends on belief updating within local social networks. I test these predictions using a randomised field experiment in dense urban neighbourhoods in Lahore, Pakistan, where enforcement capacity is limited and policy relies on public visibility rather than formal monitoring. The intervention combines free access with repeated, highly visible reinforcement at central public locations. Compliance increases sharply during the intervention but declines after visibility is withdrawn. However, this decay is highly heterogeneous: socially cohesive communities exhibit significantly slower attenuation despite similar initial responses. The results show that temporary visibility can substitute for enforcement in the short run, but its effectiveness depends critically on local social structure. Identical interventions generate similar contemporaneous effects but diverge sharply in persistence, implying that policy impact is governed not only by take-up but by the dynamics of belief updating and coordination. Welfare counterfactuals indicate that short, targeted interventions in cohesive environments can generate large and cost-effective gains. These findings highlight a central constraint in low-capacity settings: policies that rely on visibility rather

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than enforcement operate through equilibrium responses that may unravel unless supported by social structure. Understanding these dynamics is key to designing effective public interventions when monitoring and enforcement are limited.

Keywords: Visibility; Network Diffusion; Dynamic Persistence; Networks; Field Experiment; Density; Spillovers.
JEL Codes: D83, H41, C93, I18, O15

1 Introduction

Many policies rely on visibility rather than enforcement to induce socially desirable behaviour. Such interventions are attractive precisely because they operate without continuous monitoring or penalties. A large empirical literature shows that visible policies can generate rapid behavioural responses across domains ranging from energy conservation and tax compliance to health behaviour and public safety. Yet a central question remains unresolved: do visible policies induce durable input adoption, or does compliance unravel once public reinforcement fades?

This question is particularly salient in dense urban environments. Cities concentrate people, compress social space, and create natural focal points for broadcasting behavioural cues. At the same time, urban interactions are often anonymous, enforcement is weak, and social ties are heterogeneous. These features make cities both promising and fragile environments for visibility-based policy. A temporary intervention may catalyse large short-run behavioural change by leveraging crowding and observability, but whether such change persists once visibility fades depends on how individuals update beliefs about others' behaviour and whether local social structure sustains coordination over time.

This paper studies the diffusion and decay of non-market inputs uptake when policy relies on temporary, highly visible interventions in dense urban settings. I focus on behaviours that are welfare-enhancing yet individually costly and weakly enforceable, such as proper mask wearing during a public-health crisis. While existing evidence shows that observability can trigger adoption, much less is known about what happens after visible reinforcement is withdrawn. Persistence is often implicitly assumed or treated as a reduced-form outcome, but without a clear framework for understanding when compliance endures and when it decays. Figure 1 previews the mechanism: visible reinforcement shifts a compliance threshold, activating a band of marginal individuals

who comply only while observability remains high

I develop a dynamic coordination framework that clarifies this distinction. Individuals face a costly decision to comply with a non-market input whose payoff depends on both private benefits and social incentives. Visibility increases contemporaneous compliance by raising observability of others' actions, thereby increasing the perceived prevalence of the behaviour among peers. However, visibility is inherently transient. Once public reinforcement ends, compliance evolves endogenously through belief updating within local networks. In cohesive communities, repeated interaction and shared reference points slow the erosion of beliefs about peer compliance, temporarily sustaining behaviour even in the absence of continued policy effort. In less cohesive environments, beliefs unravel quickly and compliance decays toward baseline.

A key implication of this framework is that persistence does not reflect permanent preference change or habit formation. Instead, persistence arises as an equilibrium phenomenon sustained by social interaction. Identical visibility shocks can therefore generate similar contemporaneous responses across communities while producing sharply different post-intervention dynamics. This distinction is central for policy design: interventions that maximise peak adoption need not maximise welfare if compliance decays rapidly once visibility fades.

I test these ideas using a large-scale randomised field experiment embedded in dense urban neighbourhoods. The intervention bundles free access with repeated, highly visible public reinforcement delivered at central public locations such as markets and mosques. The design intentionally combines low private cost with high observability, reflecting how many real-world policies operate when enforcement capacity is limited. Behaviour is observed unobtrusively at multiple sites within each neighbourhood on a weekly basis, allowing me to track both contemporaneous responses during the active intervention period and post-intervention dynamics once reinforcement ends.

The experiment yields three main findings. First, visible reinforcement generates a large and precisely estimated increase in compliance while active. The magnitude of this effect is economically meaningful relative to baseline levels and comparable to the upper bound of behaviourally induced changes documented in similar settings. Second, once visible reinforcement ends, compliance does not immediately revert to baseline. Instead, behaviour partially persists and then attenuates over time. This pattern rules out purely transitory responses while also rejecting permanent input adoption. Third, and most importantly, the speed of post-intervention decay varies sharply across communities. Socially cohesive neighbourhoods exhibit significantly slower attenuation despite similar contemporaneous responses, whereas compliance decays rapidly in less cohesive environments.

These patterns are difficult to reconcile with explanations based on information provision, habit formation, or differential exposure. Instead, they align closely with the framework's interpretation of visibility as a temporary coordination device whose effects persist only insofar as social interaction sustains beliefs about others' behaviour. Where cohesion is high, repeated encounters reinforce expectations and slow decay. Where cohesion is low, beliefs revert quickly once public cues disappear.

To characterise these dynamics, I estimate a parsimonious reduced-form decay process that summarises how treatment effects attenuate after reinforcement ends. I emphasise that the estimated decay parameter captures equilibrium-level behavioural erosion driven by declining observability and belief updating, not a deep structural preference or learning parameter. This disciplined interpretation allows the empirical analysis to remain transparent while still yielding economically meaningful insights about persistence.

I then use the estimated dynamics to conduct welfare counterfactuals evaluating alternative intervention durations and targeting strategies. These counterfactuals reveal a central trade-off. Extending the duration of visible reinforcement increases contemporaneous compliance but yields diminishing returns when decay is rapid. In contrast,

short, visible interventions can generate substantial welfare gains when directed toward socially cohesive communities, where endogenous reinforcement sustains behaviour beyond the active period. These results suggest that optimal policy design depends not only on the intensity or duration of intervention, but critically on the social structure of targeted communities.

This paper contributes to several literatures. First, it advances work on non-market input provision by shifting attention from static treatment effects to dynamic persistence and decay. Second, it contributes to the study of social interactions by showing how local cohesion governs the durability of compliance once external reinforcement ends. Third, it informs policy design in low-capacity settings by clarifying when temporary visibility can substitute for sustained enforcement, and when decay dominates. More broadly, the findings highlight that social structure is not merely a moderator of policy impact, but a central determinant of its dynamic effectiveness.

The remainder of the paper proceeds as follows. Section 2 reviews related literature. Section 3 presents the dynamic framework and derives testable implications. Section 4 describes the experimental setting, design, and measurement. Section 5 presents the empirical results on contemporaneous effects, persistence, and heterogeneity. Section 6 discusses welfare and policy implications. Section 7 concludes.

2 Related Literature

This paper contributes to and connects four strands of research: non-market inputs and social preferences; observability; network diffusion; and urban collective behaviour.

Non-Market Inputs and Social Preferences

Classical analyses of non-market input provision highlight the divergence between private and social incentives Samuelson 1954 Bergstrom, Blume, and Varian 1986 An-

dreoni 1990. Subsequent work introduced heterogeneous motivations and conditional cooperation Fehr and Schmidt 1999 Fischbacher, Gächter, and Fehr 2001 Bénabou and Tirole 2006. While these models explain why individuals contribute less than socially optimal levels, sustaining cooperation in the absence of enforcement requires informational or reputational mechanisms that make contributions visible. The present study builds on this insight by endogenising social utility as a function of observed local compliance, thereby linking the non-market input provision to network observability.

Observability

The economics of compliance traces to Akerlof 1980, Bernheim 1994, and Young 1993 , who formalised reputation and conformity pay-offs. Visibility amplifies prosocial behaviour across domains—from charitable giving Soetevent 2005 and energy use Allcott 2011 to health behaviours Abaluck et al. 2022 Dupas 2011 Banerjee, Duflo, et al. 2019. Behavioural models emphasise that limited attention and visibility shape which cues are processed Bordalo, Gennaioli, and Shleifer 2013 Gabaix 2014.

This paper operationalises visibility as a manipulable policy variable that increases the effective weight of social utility in individual adoption thresholds. Empirically, Chetty, Looney, and Kroft 2009 and Allcott and Rogers 2014 show that visible feedback can yield large short-run responses, though effects decay without reinforcement—consistent with the dynamics observed here.

Networks and diffusion

A vast theoretical literature studies how behaviours spread through network interactions Jackson and Wolinsky 1996 Bala and Goyal 2000 Jackson 2008 Golub and Jackson 2010. Learning and diffusion depend on topology, clustering, and centrality Acemoglu and Ozdaglar 2011. Empirical evidence from development economics demonstrates strong network mediation of technology and health adoption Conley and Udry 2010 Banerjee,

Chandrasekhar, et al. 2013 Beaman et al. 2018 BenYishay and Mobarak 2019. Peer influence tends to be stronger when signals originate from central nodes or cohesive communities Kim et al. 2015. The current study differs by focusing on diffusion of a *non-market input*—a behaviour whose payoff depends on mutual participation—thereby linking network diffusion with collective-action dynamics Schelling 1978 Brock and Durlauf 2001.

Urban collective behaviour

Urban density is often associated with anonymity and weak enforcement Glaeser 2011 Duranton and Puga 2004, yet it also creates natural focal points that can accelerate diffusion if leveraged effectively Lucas 1988 Rossi-Hansberg and Wright 2007. Despite rapid urbanisation in low-income countries, causal evidence on input adoption in dense cities remains scarce. By analysing a large-scale randomised intervention that exploits existing public hubs to broadcast focal cues, this paper contributes to understanding how urban structure mediates non-market input provision and behavioural externalities.

Taken together, these literatures highlight four interacting elements that underpin collective compliance: the visibility of individual behaviour, the cohesion of local networks, the ease of physical and cognitive access, and the dynamics of reinforcement over time. The present study unifies these strands by showing how visibility and access jointly raise adoption, how network cohesion amplifies the diffusion process, and how reinforcement dynamics determine the durability of behavioural change.

3 A Dynamic Framework of Visibility, Beliefs, and Decay

This section develops a simple framework to clarify how temporary, highly visible policy interventions affect non-market input compliance over time. The objective is not

to recover deep structural preferences, but to discipline interpretation of the empirical dynamics by isolating the role of visibility, belief updating, and social interaction. The framework highlights how large contemporaneous responses and gradual post-intervention decay can arise even when preferences, costs, and enforcement remain unchanged.

3.1 Adoption, Visibility, and Social Reinforcement

Consider a population of individuals indexed by i, each choosing in period t whether to comply with a welfare-enhancing non-market input adoption rule. Compliance is individually costly but generates social benefits that depend on the behaviour of others.

Let B_p denote the private benefit of compliance (e.g. self-protection), B_s the social or reputational benefit, and C_i an individual-specific residual cost capturing time, effort, discomfort, or logistical frictions. Individuals observe compliance in their local environment. Let $\phi_i \in [0, 1]$ denote the share of peers whose *compliance is both realised and publicly observed*. Throughout, ϕ_i is interpreted as a reduced-form index of *observed peer compliance*, rather than mere observability.

An individual complies when the combined private and social returns exceed a behavioural threshold:

$$f(B_p) + (\delta_0 + \rho\phi_i)\, g(B_s) \;\geq\; T_0 + \alpha C_i, \tag{1}$$

where δ_0 captures baseline responsiveness to social considerations, $\rho > 0$ measures the strength of social reinforcement, T_0 is a fixed adoption threshold, and $\alpha > 0$ scales residual costs.

Visibility-based interventions raise contemporaneous compliance by increasing ϕ_i: individuals observe more peers complying, which increases the perceived social return to compliance. Social cohesion magnifies this effect by increasing the sensitivity of

perceived social returns to observed behaviour.

3.2 Compliance Cutoffs and the Switcher Band

Condition (1) implies a cutoff rule in individual compliance costs. For a given level of observed peer compliance ϕ, individuals comply if their cost lies below a threshold:

$$C_i \leq C(\phi) \equiv \frac{f(B_p) + (\delta_0 + \rho\phi)\, g(B_s) - T_0}{\alpha}. \tag{2}$$

Let ϕ^N denote observed peer compliance in the absence of visible reinforcement, and let $\phi^S > \phi^N$ denote the elevated observability induced by a visible intervention. This yields two thresholds:

$$C^N \equiv C(\phi^N), \qquad C^S \equiv C(\phi^S), \tag{3}$$

with $C^S > C^N$.

The population therefore partitions into three groups:

1. **Always-compliers**: individuals with $C_i \leq C^N$, who comply regardless of visibility.
2. **Never-compliers**: individuals with $C_i > C^S$, who do not comply even under visible reinforcement.
3. **Salience-switchers**: individuals with

$$C^N < C_i \leq C^S,$$

who comply only when visibility is high.

The interval $(C^N, C^S]$ constitutes the *switcher band*. Individuals in this band appear non-compliant under low visibility but are willing to comply when public reinforcement raises perceived peer compliance.

This cutoff structure clarifies the nature of observed behavioural change. Large contemporaneous responses arise because visible interventions activate a mass of individuals near the compliance margin, not because preferences or costs shift.

3.3 Belief Updating and Dynamic Complementarities

Observed compliance feeds back into beliefs about future behaviour. Let c_t denote the realised compliance rate in period t, and let $E_t[c_{t+1}]$ represent expectations about future compliance. Beliefs update according to:

$$E_t[c_{t+1}] = (1 - \lambda)\, E_{t-1}[c_t] + \lambda\, c_t, \tag{4}$$

where $\lambda \in (0, 1)$ governs the weight placed on contemporaneous observations relative to past beliefs.

Higher values of λ correspond to stronger social cohesion: individuals place more weight on observed local behaviour when forming expectations. During the active intervention period, visibility raises c_t, which in turn increases expected compliance, generating dynamic complementarities that sustain elevated adoption.

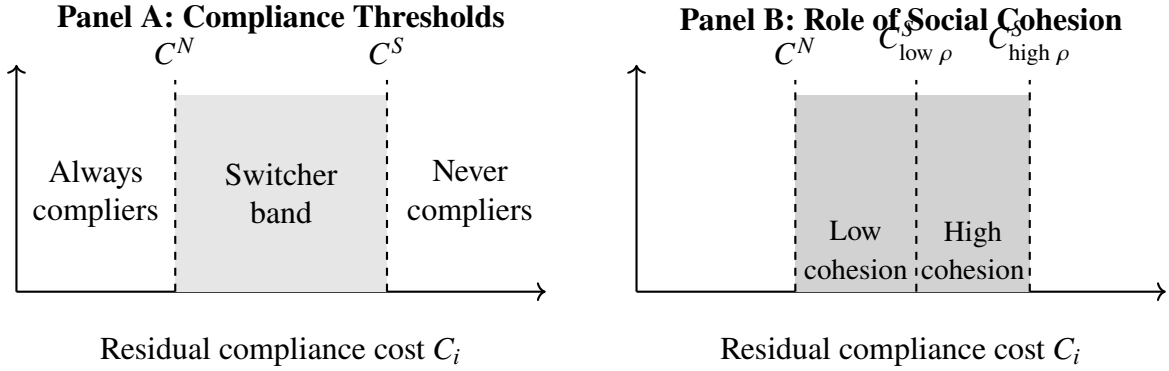


Figure 1: **Compliance thresholds and the switcher band.** Panel A illustrates individual compliance decisions as a function of residual compliance costs C_i. Under low visibility, individuals comply if $C_i \leq C^N$. A visible intervention raises observed peer compliance, shifting the threshold to C^S. Individuals with costs in $(C^N, C^S]$ comply only while salience is active (the switcher band). When visibility fades, the threshold reverts and switchers exit compliance, generating decay. Panel B shows that higher social cohesion expands the salience-induced threshold shift, widening the switcher band and slowing post-intervention decay.

3.4 Post-Intervention Decay

Visible reinforcement is temporary. Once public cues are withdrawn, observability declines from ϕ^S back toward ϕ^N. As a result, the compliance threshold reverts mechanically from C^S to C^N.

Individuals in the switcher band therefore exit compliance as beliefs update downward. Aggregate compliance attenuates over time as elevated expectations erode. Importantly, this decay does *not* reflect habit loss, preference change, or learning reversal. It is an equilibrium outcome driven by declining observability and belief updating under unchanged primitives.

Persistence arises because beliefs do not collapse instantaneously. As long as past compliance continues to influence expectations through equation (2), behaviour remains temporarily elevated. Decay reflects the gradual erosion of this influence once reinforcement ends.

3.5 Social Cohesion and Heterogeneous Decay

Social cohesion shapes post-intervention dynamics through two channels. First, higher cohesion increases the responsiveness of perceived social returns to observed behaviour, expanding the salience-induced shift in the compliance threshold $C^S - C^N$. This widens the switcher band, increasing the mass of individuals who respond to visibility.

Second, cohesion affects belief updating. Higher λ slows the erosion of expectations by placing greater weight on contemporaneous local behaviour. Together, these forces imply that identical visibility shocks can generate similar contemporaneous responses across communities while producing sharply different decay paths once reinforcement ends. In the empirical application, the cohesion measures used below are more closely aligned with the belief-updating channel than with the salience-amplification channel. While cohesion can in principle also widen the switcher band by amplifying the salience-

induced threshold shift, the baseline cohesion proxies capture the extent of coordination and feedback across social spaces rather than the mass of marginal adopters. As a result, the framework does not generate a strong prediction that contemporaneous treatment effects must differ sharply across cohesion levels, even though post-intervention decay rates may diverge substantially.

In cohesive environments, a larger switcher band and slower belief erosion sustain compliance beyond the active intervention period. In less cohesive environments, the switcher band is narrow and beliefs unravel quickly, leading to rapid decay.

3.6 Mapping the Framework to Empirical Objects

The empirical analysis maps directly to the framework's components. Contemporaneous treatment effects identify the activation of the switcher band during the visible intervention period. Event-study estimates trace the evolution of compliance as beliefs update and observability fades.

Social cohesion is proxied using pre-intervention coordination in behaviour across observation sites within neighbourhoods. This proxy is interpreted as capturing the strength of local belief reinforcement and feedback, rather than differences in baseline compliance levels or mechanical exposure to visibility. Post-intervention attenuation is summarised by a reduced-form decay parameter that captures the speed at which compliance erodes once reinforcement ends. This parameter is interpreted as an equilibrium-level measure of behavioural decay driven by declining visibility and belief updating, not as a deep structural preference or learning parameter.

The framework yields three testable implications. First, visibility increases compliance while reinforcement is active. Second, identical visibility shocks generate similar contemporaneous responses but different persistence across social environments. Third, welfare depends not on peak compliance alone, but on the interaction between decay and social structure.

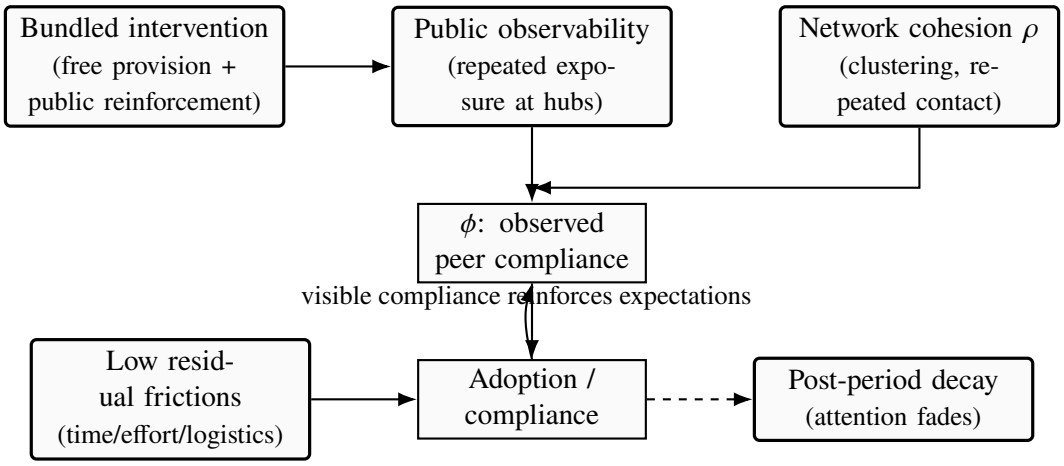


Figure 2: Conceptual map: the bundled programme raises observability and lowers frictions; observed peer compliance ϕ and cohesion ρ amplify adoption; effects attenuate when observability fades.

4 Experimental Design

The experiment tests whether a *single, bundled intervention*—combining free distribution of the target good with continuous, highly visible public reinforcement—shifts a welfare-enhancing behaviour in dense urban clusters. In dense urban environments, ease of access and observability are not separable policy margins: behaviours that are easy to perform are also more likely to be observed in shared public spaces. The intervention therefore targets the composite channel through which access and visibility jointly shift equilibrium adoption.

Setting and sampling. Thirty geographically contiguous urban subdivisions (clusters) constitute the experimental universe. Prior to randomisation, a baseline enumeration established sampling frames, mapped observation sites (markets and mosques), and recorded pre-intervention compliance.

Randomisation. Clusters were stratified by baseline compliance and network cohesion, then randomly assigned to *Treatment* (15 clusters) or *Control* (15 clusters). Treatment clusters received the bundled programme; control clusters did not during the study window. Randomisation checks indicate no systematic baseline differences (1).

Table 1 shows that treatment and control clusters were well balanced on all baseline compliance measures. Average pre-intervention compliance across all observation points ("Baseline total") was 19.4 percent in control areas and 17.2 percent in treatment areas; the difference of 2.3 percentage points is statistically insignificant ($p = 0.49$). When disaggregated by observation site, baseline mask use was nearly identical in markets—19.7 percent in control versus 19.4 percent in treatment clusters ($p = 0.92$)—and modestly higher in control than treatment clusters at mosques (16.1 percent vs. 10.6 percent, $p = 0.18$). These results confirm that randomisation achieved ex ante comparability across clusters and that any post-intervention differences can be attributed to the

Table 1: Baseline balance across treatment and control clusters

Variable	Control mean	Treatment mean	P-value
Baseline (total)	19.423	17.155	0.490
	(8.823)	(8.936)	
Baseline (market)	19.677	19.356	0.924
	(9.528)	(8.564)	
Baseline (mosque)	16.069	10.565	0.175
	(10.458)	(11.216)	

Notes: Table reports pre-intervention means for observed compliance across control and treatment clusters, with standard deviations in parentheses. p-values come from cluster-level regressions of the baseline variable on the treatment indicator. All baseline data were collected during the pre-intervention week using identical observation protocols across sites.

experimental treatment rather than pre-existing variation.

Intervention. The programme was delivered uniformly within treated clusters over eight weeks. It consisted of (i) costless doorstep delivery and public availability of the good, and (ii) continuous reinforcement at central public hubs (markets, mosques, transport nodes) via signage and audible announcements delivered by recognised community figures. Because both components were intentionally deployed together to maximise visibility at low private cost, the empirical contrast is *Treatment vs. Control* only.

Outcomes and timing. Enumerators recorded behaviour at pre-specified sites weekly for ten weeks: eight weeks during implementation and two post-period weeks. Observation protocols and enumerator rotation were standardised across clusters and time.

Data quality and quality assurance. Enumerators underwent a week of classroom and field training prior to the intervention. Daily electronic back-checks and GPS-timestamp verification ensured data integrity, with random audits covering roughly ten per cent of observations each week.

Inference. All randomisation units were observed throughout; the panel is complete. Standard errors are clustered at the cluster level. Spillovers across clusters are plausibly limited by distance.

5 Empirical Strategy

This section describes how I estimate contemporaneous treatment effects, dynamic persistence, heterogeneity by social cohesion, and post-intervention decay. The empirical strategy is designed to mirror the dynamic coordination framework developed in Section 3 and to discipline interpretation of reduced-form estimates.

5.1 Experimental Design and Data Structure

The analysis uses data from a randomised field experiment implemented at the subdivision level. Subdivisions were randomly assigned to treatment or control prior to the intervention. Within each subdivision, behaviour is observed weekly at two central public locations—a market and a mosque—yielding repeated observations over time and within neighbourhoods.

The intervention bundles free access with repeated, highly visible public reinforcement delivered during a finite active period. After the intervention ends, no further reinforcement is provided. This design allows me to separately identify contemporaneous responses to visibility and post-intervention dynamics driven by belief updating.

The unit of observation is a subdivision–location–week cell. All specifications exploit within-subdivision variation over time and cluster standard errors at the subdivision level to account for serial correlation and spatial dependence.

5.2 Average and Dynamic Treatment Effects

I estimate average treatment effects using a difference-in-differences specification of the form:

$$y_{slt} = \alpha_s + \gamma_t + \beta_1 \text{Treat}_s \times \text{Active}_t + \beta_2 \text{Treat}_s \times \text{After}_t + \varepsilon_{slt},$$

where y_{slt} denotes the share of proper compliance in subdivision s, location l, and week t. Subdivision fixed effects α_s absorb time-invariant neighbourhood characteristics, and week fixed effects γ_t capture common temporal shocks.

To characterise dynamics flexibly, I estimate an event-study specification that allows treatment effects to vary by week relative to the start of the intervention. This specification serves two purposes. First, it tests for differential pre-trends between treatment and control subdivisions. Second, it traces the evolution of treatment effects during the active period and after reinforcement ends, providing a non-parametric view of persistence and decay.

5.3 Social Cohesion and Heterogeneity

The model predicts that post-intervention persistence depends on the strength of local social interactions. To test this implication, I exploit heterogeneity in baseline social cohesion across subdivisions.

I proxy cohesion using the pre-intervention correlation in proper compliance between market and mosque locations within the same subdivision. This measure captures the extent to which behaviour is internally coordinated rather than location-specific. I classify subdivisions into high- and low-cohesion groups based on the median of this distribution.

I then estimate treatment effects separately by cohesion group and interact treatment indicators with the cohesion measure in pooled specifications. This approach isolates

whether persistence differs across social environments despite similar contemporaneous exposure to the intervention.

In addition to our continuous proxy for social cohesion, I exploit a second, institutionally grounded measure of cohesiveness that arises naturally in the study context: whether compliance is observed in mosques rather than markets. Mosques function as highly cohesive social units. They are characterised by repeated interactions among a stable group of individuals, shared adoption rules and rituals, and a focal authority structure, all of which facilitate belief coordination and mutual monitoring. In contrast, markets involve more anonymous and transient interactions, with weaker informational feedback. Consistent with this interpretation, I observe substantially higher contemporaneous uptake in mosques relative to markets during the intervention period.

This difference is not driven by mechanical exposure to treatment or differential baseline trends. Both location types receive identical policy intensity and timing, and event-study estimates show no evidence of differential pre-trends. Instead, the higher uptake in mosques is consistent with a setting in which visibility more effectively shifts higher-order beliefs about compliance, enabling coordination on the compliant equilibrium. In this sense, location type serves as a coarse but intuitive proxy for social cohesion.

Importantly, mosque-based cohesion captures a distinct dimension of social structure than the continuous cohesion measure used elsewhere in the paper. While the latter reflects network density and overlap at the subdivision level, mosque interactions operate at a finer institutional scale and are tied to shared collective observance. The two measures therefore complement rather than substitute for each other. The fact that both independently predict stronger compliance responses reinforces the interpretation that persistence is governed by belief dynamics within cohesive social environments, rather than by enforcement or habit formation. Taken together, the location-based and network-based measures point to the same conclusion: environments that facilitate repeated interaction and shared expectations exhibit both higher initial compliance and

greater resistance to post-intervention decay.

5.4 Reduced-Form Decay Estimation

To summarise post-intervention dynamics parsimoniously, I estimate a reduced-form decay specification that models the attenuation of treatment effects after visible reinforcement ends. Specifically, I regress post-intervention compliance on an exponentially declining function of time since treatment withdrawal, allowing me to recover a decay parameter λ that governs the speed of attenuation.

This specification abstracts from individual-level learning or preference change and instead captures equilibrium-level behavioural erosion driven by declining visibility and belief updating. As discussed in Section 3.4, λ is interpreted as a reduced-form summary of attenuation rather than a deep structural parameter.

5.5 Welfare Counterfactuals

Finally, I use the estimated dynamic responses to conduct welfare counterfactuals that evaluate alternative intervention durations and targeting strategies. Using the estimated decay process, I simulate compliance paths under different lengths of visible reinforcement and compute aggregate compliance net of intervention costs.

This exercise allows me to compare short intervention pulses with longer or permanent reinforcement and to assess how welfare gains vary with social cohesion. The counterfactuals are partial equilibrium and intended to inform policy design rather than identify optimal policy in a fully general equilibrium setting.

6 Results

6.1 Average Treatment Effects

I begin by estimating the average effect of the intervention on proper compliance using a difference-in-differences specification with subdivision and week fixed effects. Standard errors are clustered at the subdivision level.

During the active intervention period, treated subdivisions exhibit a large and precisely estimated increase in proper compliance relative to control areas. The treatment effect is economically meaningful, corresponding to an increase of approximately nine percentage points over baseline levels. This magnitude is substantial given the low baseline rate of compliance and reflects the strong contemporaneous impact of access combined with repeated visible reinforcement.

After the intervention ends, compliance declines but remains elevated relative to control. The post-intervention treatment effect is smaller in magnitude than the active-period effect, consistent with attenuation once reinforcement is withdrawn. Importantly, the effect does not immediately revert to zero, indicating partial persistence rather than a purely transitory response.

These results establish two core facts: the intervention is highly effective while active, and its effects attenuate but do not vanish immediately after withdrawal.

6.2 Dynamic Treatment Effects

To examine the evolution of treatment effects over time, I estimate an event-study specification that allows treatment effects to vary flexibly by week.

Table 2: Treatment Effects on Proper Mask Wearing (Subdivision Level)

	Markets	Mosques	Overall
Treatment	3.680**	6.684**	4.477**
	(1.560)	(2.464)	(1.669)
Observations	30	30	30
Strata Controls	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes

Notes: This table reports subdivision-level treatment effects of a salient enforcement intervention on proper mask wearing. Data were collected through structured observations conducted in markets and mosques at multiple times throughout the day. The dependent variable is the proportion of individuals observed wearing masks properly. Each column reports estimates from a separate regression using the same underlying sample, restricted to the indicated setting or pooled across settings. All specifications control for randomization strata and baseline mask-wearing measures. Robust standard errors are reported in parentheses. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Difference-in-Differences Estimates with Subdivision and Week Fixed Effects

	Mosques	Markets
Treatment × Active	0.131^{***}	0.053^{**}
	(0.035)	(0.020)
Treatment × After	0.174^{***}	0.042^{*}
	(0.061)	(0.024)
Subdivision Fixed Effects	Yes	Yes
Week Fixed Effects	Yes	Yes

Notes: This table reports difference-in-differences estimates of the impact of a salient enforcement intervention on proper mask wearing. The unit of observation is a subdivision–location–week cell, with standard errors clustered at the subdivision level. The dependent variable is the proportion of individuals observed wearing masks properly, measured through structured observations conducted in markets and mosques at multiple times throughout the day. *Active* denotes weeks during which the intervention was in place, while *After* denotes post-intervention weeks. All specifications include subdivision and calendar-week fixed effects. Robust standard errors are reported in parentheses. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

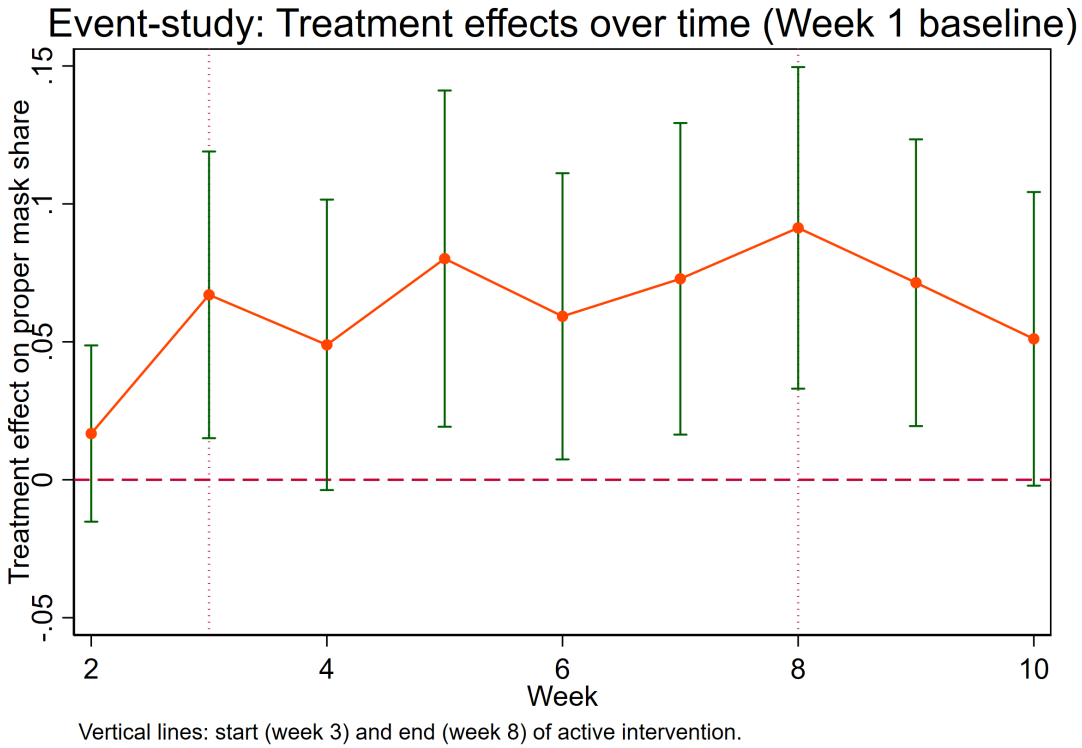


Figure 3: Overall event-study estimates of treatment effects over time. This figure plots event-study coefficients from a difference-in-differences specification estimating the impact of the bundled access and salience intervention on proper compliance, pooled across observation locations. The unit of observation is a subdivision–week. Coefficients are normalised relative to the omitted pre-intervention week (week 1). Vertical dashed lines indicate the start (week 3) and end (week 8) of the active intervention period. Error bars represent 95% confidence intervals with standard errors clustered at the subdivision level. Post-intervention estimates are based on the two weeks following the withdrawal of visible reinforcement (weeks 9–10) and illustrate partial persistence with gradual attenuation rather than immediate reversion.

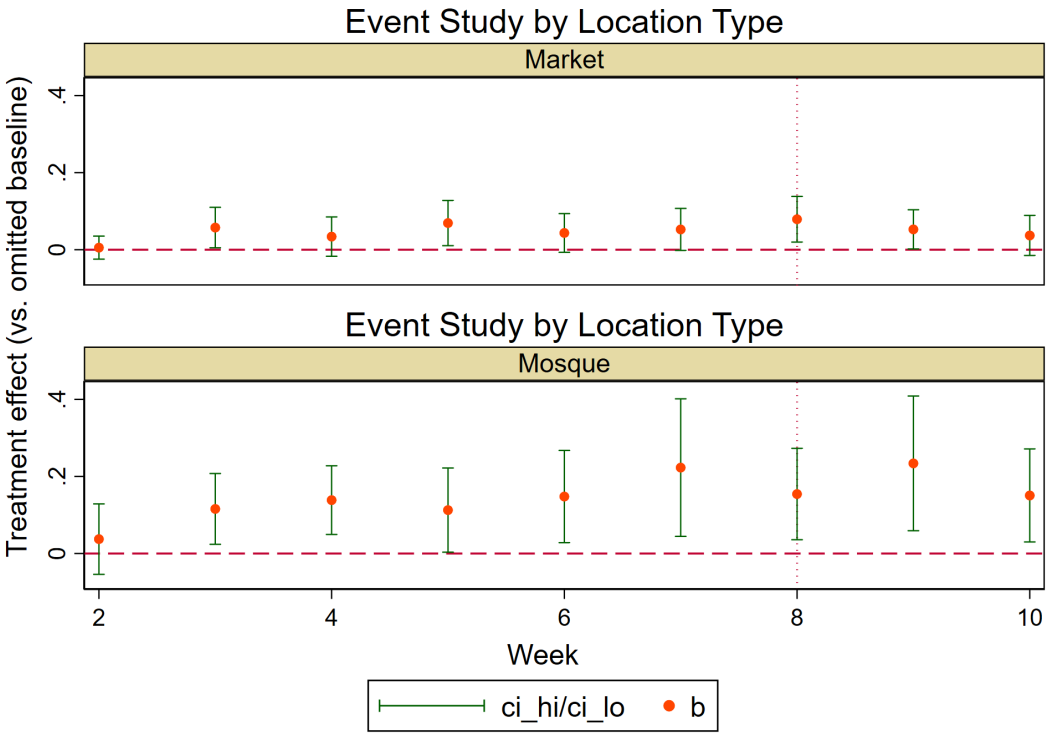


Figure 4: Event-study estimates by location type. This figure reports event-study coefficients separately for market and mosque observation sites. Specifications are identical across panels and mirror the pooled event-study in Figure 3, with coefficients normalised to the omitted pre-intervention week. Vertical dashed lines mark the start (week 3) and end (week 8) of the active intervention. Error bars denote 95% confidence intervals with standard errors clustered at the subdivision level. Both locations exhibit similar contemporaneous responses during the intervention period, while post-intervention dynamics differ in magnitude, consistent with stronger persistence in more cohesive social environments.

The dynamic estimates show no evidence of differential pre-trends between treatment and control subdivisions prior to the intervention. Following the onset of treatment, compliance rises sharply and remains elevated throughout the active period. The treatment effect peaks toward the latter weeks of reinforcement, suggesting cumulative effects of repeated exposure.

Once reinforcement ends, the treatment effect declines monotonically. However, compliance remains significantly above control levels for several weeks, before gradually converging toward baseline. This pattern is inconsistent with permanent habit formation or a stable shift in preferences, but is consistent with endogenous reinforcement that weakens as visibility fades.

Overall, the event-study estimates support the model's prediction of strong contemporaneous adoption followed by partial persistence with decay.

6.3 Heterogeneity by Social Cohesion

The model predicts that post-intervention dynamics depend on local social structure. To test this implication, I examine heterogeneity in treatment effects by baseline social cohesion, measured as the correlation in proper compliance between market and mosque locations within a subdivision.

During the active intervention period, treatment effects are similar across high- and low-cohesion subdivisions. This indicates that visible reinforcement operates broadly and does not require pre-existing social cohesion to generate contemporaneous adoption.

In contrast, post-intervention dynamics differ sharply across communities. In high-cohesion subdivisions, compliance decays more slowly and remains elevated for longer after reinforcement ends. In low-cohesion areas, treatment effects attenuate rapidly and approach zero within a few weeks.

These results highlight the role of social interactions in sustaining behaviour once exter-

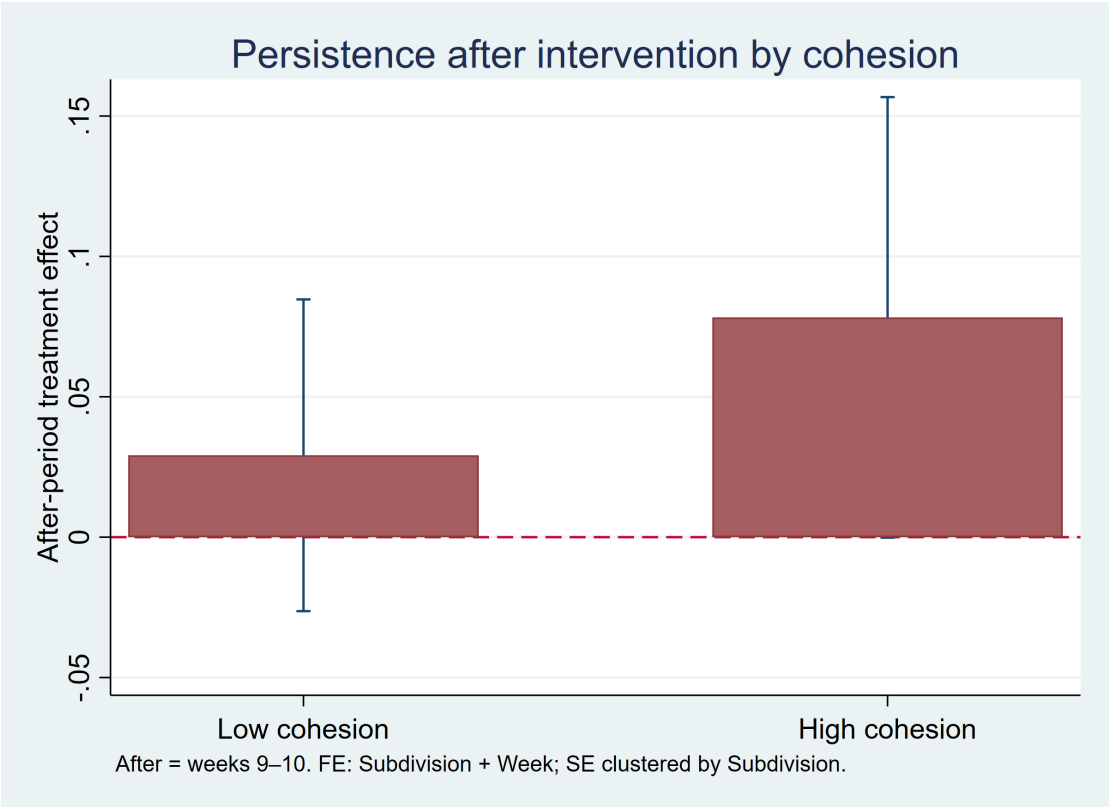


Figure 5: Post-intervention persistence by social cohesion. This figure plots estimated post-intervention treatment effects on proper compliance separately for low- and high-cohesion subdivisions. Cohesion is measured using the pre-intervention correlation in compliance between market and mosque observation sites within a subdivision and dichotomised at the median. Bars correspond to the estimated coefficient on *Treatment* $\times$ *After* from a difference-in-differences specification with subdivision and week fixed effects; whiskers denote 95% confidence intervals based on standard errors clustered at the subdivision level. The post-intervention period comprises the two weeks following the end of visible reinforcement (weeks 9–10). While contemporaneous treatment effects are similar across cohesion groups, post-intervention compliance persists more strongly in high-cohesion environments, consistent with slower belief erosion under stronger local coordination.

Table 4: Social Cohesion and Persistence of Compliance (ρ Proxy)

	Proper Mask Wearing
Treatment × Active × High Cohesion	0.008
	(0.047)
Treatment × After × High Cohesion	0.120*
	(0.067)
Observations	594

Notes: This table examines heterogeneity in treatment effects by social cohesion, a proxy for the persistence parameter ρ in the model. The dependent variable is the proportion of individuals observed wearing masks properly. *High Cohesion* is an indicator for subdivisions with above-median social cohesion, measured using pre-intervention neighborhood characteristics. *Active* denotes periods during which the intervention was in place, while *After* denotes post-intervention periods. All specifications include the baseline main effects and fixed effects used in the corresponding difference-in-differences specification. Robust standard errors are reported in parentheses. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

nal cues are removed. Persistence arises not from differential exposure or enforcement, but from local coordination that reinforces beliefs about others' behaviour.

The cohesion measure captures coordination across social spaces rather than attitudes or preferences. High correlation in compliance across markets and mosques indicates that behavioural signals propagate across otherwise distinct interaction domains, consistent with tighter local feedback loops rather than stronger intrinsic adoption rules

6.4 Reduced-Form Decay

To summarise post-intervention dynamics parsimoniously, I estimate a reduced-form decay specification that models the attenuation of treatment effects after reinforcement ends.

The estimated decay rate is positive, indicating gradual attenuation rather than abrupt reversion. The implied half-life is less than one week, underscoring that persistence is limited in duration. At the same time, the decay is sufficiently slow to generate meaningful cumulative effects in high-cohesion communities.

I emphasise that the decay parameter is not interpreted as a deep preference parameter.

Rather, it captures reduced-form attenuation driven by declining visibility and belief updating in the absence of reinforcement. The estimates therefore quantify the speed of behavioural erosion, not the permanence of adoption rules.

7 Welfare Counterfactuals

This section quantifies the welfare implications of short, highly visible policy interventions when behavioural responses persist but decay over time. Using the reduced-form decay process estimated, we construct a set of transparent counterfactuals that isolate the contribution of post-intervention persistence to cumulative welfare. All counterfactuals hold fixed the contemporaneous treatment effect and vary only the post-intervention decay rate.

7.1 Setup

Let c_0 denote baseline compliance in the absence of treatment. The intervention generates an immediate increase in compliance of magnitude A, followed by exponential decay at rate λ. The compliance path in treated areas is given by

$$c(t) = c_0 + Ae^{-\lambda t}. \tag{5}$$

Compliance is mapped into flow welfare using a linear function,

$$W(t) = \phi \cdot c(t), \tag{6}$$

where ϕ is a constant that converts compliance into welfare units. Because ϕ is common across counterfactuals, welfare comparisons depend only on differences in compliance paths. We compute cumulative welfare over a fixed horizon T.

7.2 Counterfactual 1: No Intervention

The first counterfactual sets the treatment amplitude to zero, $A = 0$, yielding a flat compliance path:

$$c^{\text{NoPolicy}}(t) = c_0. \tag{7}$$

This scenario represents the status quo in the absence of any visible intervention. Cumulative welfare is given by

$$W^{\text{NoPolicy}} = \int_0^T \phi \cdot c_0 \, dt. \tag{8}$$

This serves as the benchmark against which all other counterfactuals are evaluated.

7.3 Counterfactual 2: Observed Temporary Intervention

The second counterfactual applies the empirically estimated amplitude A and decay rate λ:

$$c^{\text{Observed}}(t) = c_0 + Ae^{-\lambda t}. \tag{9}$$

This corresponds to the actual policy implemented in the experiment: a short, highly visible intervention that raises compliance immediately and induces partial persistence after visibility ends. Cumulative welfare is

$$W^{\text{Observed}} = \int_0^T \phi \left(c_0 + Ae^{-\lambda t} \right) dt. \tag{10}$$

The difference $W^{\text{Observed}} - W^{\text{NoPolicy}}$ captures the total welfare gain generated by the intervention, inclusive of post-intervention persistence.

7.4 Counterfactual 3: No Persistence

To isolate the role of persistence, we consider a counterfactual in which compliance responds only contemporaneously to visibility, with no post-intervention persistence. Formally, this corresponds to the limit $\lambda \to \infty$, so that

$$c^{\text{NoPersistence}}(t) = \begin{cases} c_0 + A & \text{if } t = 0, \\ c_0 & \text{if } t > 0. \end{cases} \tag{11}$$

Cumulative welfare collapses to the one-period gain at the time of the intervention,

$$W^{\text{NoPersistence}} \approx \phi(c_0 + A). \tag{12}$$

Comparing this counterfactual to the observed intervention isolates the welfare contribution of post-intervention persistence:

$$W^{\text{Observed}} - W^{\text{NoPersistence}}. \tag{13}$$

7.5 Counterfactual 4: Slower Decay

We next consider a counterfactual with a lower decay rate, $\lambda' < \lambda$, holding the contemporaneous treatment effect fixed:

$$c^{\text{SlowerDecay}}(t) = c_0 + Ae^{-\lambda' t}. \tag{14}$$

This counterfactual captures how the same intervention would perform in a more cohesive environment where compliance attenuates more slowly. Cumulative welfare

is

$$W^{\text{SlowerDecay}} = \int_0^T \phi\left(c_0 + Ae^{-\lambda' t}\right) dt. \tag{15}$$

7.6 Counterfactual 5: Faster Decay

Finally, we consider an environment with more rapid attenuation, characterized by a higher decay rate $\lambda'' > \lambda$:

$$c^{\text{FasterDecay}}(t) = c_0 + Ae^{-\lambda'' t}. \tag{16}$$

This counterfactual captures how the same visible intervention would perform in less cohesive settings. Cumulative welfare is given by

$$W^{\text{FasterDecay}} = \int_0^T \phi\left(c_0 + Ae^{-\lambda'' t}\right) dt. \tag{17}$$

7.7 Summary Measures

To summarise the welfare implications, we report (i) baseline welfare W^{NoPolicy}, (ii) welfare under the observed intervention W^{Observed}, and (iii) welfare under no persistence $W^{\text{NoPersistence}}$. A key object of interest is the share of total welfare gains attributable to persistence:

$$\text{Persistence Share} = \frac{W^{\text{Observed}} - W^{\text{NoPersistence}}}{W^{\text{Observed}} - W^{\text{NoPolicy}}}. \tag{18}$$

This ratio quantifies the extent to which welfare gains from visible interventions arise from post-intervention persistence rather than contemporaneous behavioural responses alone.

Figure 6 illustrates cumulative welfare under alternative persistence counterfactuals constructed using the estimated decay process. All counterfactuals hold fixed the contemporaneous treatment effect and differ only in the rate at which compliance attenuates

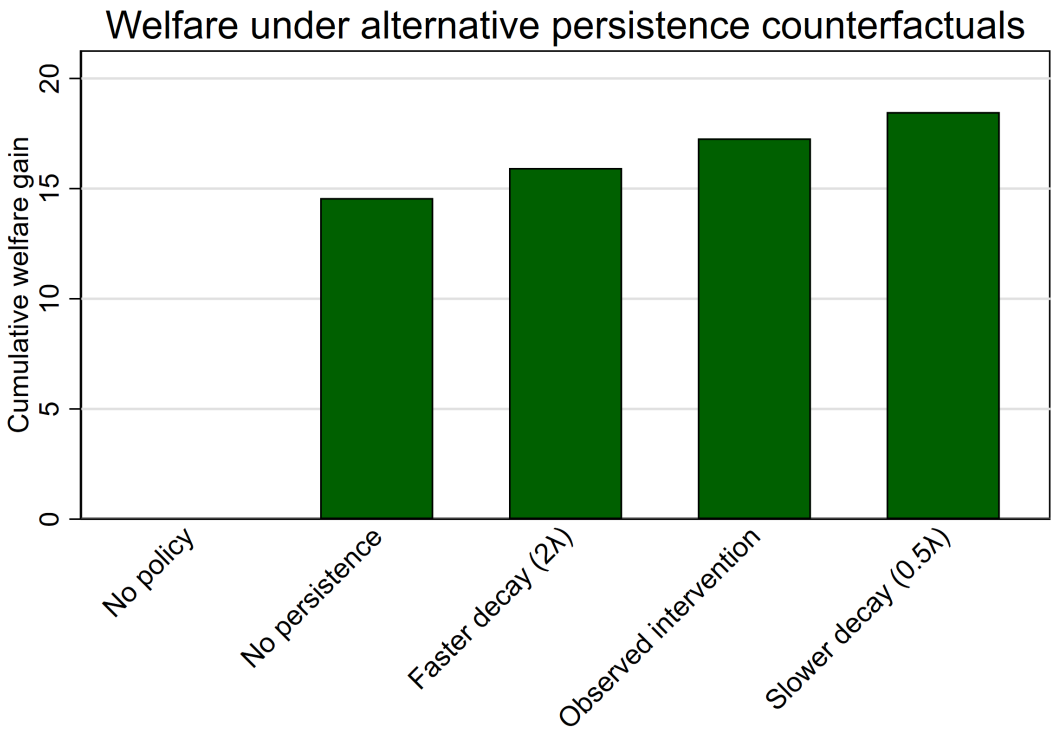


Figure 6: Cumulative welfare under alternative persistence counterfactuals. This figure plots cumulative welfare implied by alternative post-intervention compliance paths constructed using the reduced-form decay process described in Section 7. Welfare is proportional to the area under the compliance path over a fixed horizon and is normalised relative to the no-policy benchmark. All counterfactuals hold fixed the contemporaneous treatment effect and differ only in the rate at which compliance attenuates after visible reinforcement ends. The *No persistence* scenario assumes immediate reversion to baseline following the intervention, while the *Faster decay* and *Slower decay* scenarios rescale the estimated decay rate to reflect environments with weaker or stronger endogenous reinforcement. The figure illustrates that welfare depends critically on post-intervention persistence rather than peak compliance alone: rapid decay substantially attenuates cumulative gains, while slower decay amplifies welfare even when intervention duration is short. The counterfactuals are partial-equilibrium and intended to inform comparative policy design rather than identify an optimal policy.

after visible reinforcement ends. Welfare is lowest in the absence of any intervention and increases monotonically with the degree of post-intervention persistence. A purely contemporaneous response with no persistence generates limited cumulative gains despite a large short-run effect. Faster decay substantially attenuates welfare relative to the observed intervention, while slower decay yields markedly larger gains. The observed intervention lies strictly between these benchmarks, indicating that while persistence contributes meaningfully to welfare, a substantial share of potential gains is lost to post-intervention decay. These comparisons underscore that welfare depends not on peak compliance alone, but on the interaction between persistence and social structure. Interpreted through the lens of the framework, the slower-decay counterfactual corresponds to a more cohesive social environment in which beliefs about peer compliance erode gradually, whereas faster decay captures settings with weaker coordination and rapid belief unraveling. The welfare ranking therefore maps directly into the heterogeneity results: identical visible interventions can generate similar contemporaneous responses yet yield sharply different cumulative benefits depending on local social structure. This highlights why targeting visibility-based policies toward cohesive networks can substantially amplify welfare even without extending the duration of reinforcement. Figure 6 shows that welfare rises monotonically with post-intervention persistence, with the observed intervention lying between fast- and slow-decay benchmarks, implying that decay—not peak compliance—is the primary determinant of cumulative welfare.

8 Welfare and Policy Design

This section interprets the welfare counterfactuals and draws implications for the design of visibility-based policy in settings with limited enforcement capacity. The analysis is intentionally partial-equilibrium and comparative in nature. Rather than characterising an optimal policy in a fully specified planner problem, the objective is to clarify how post-intervention persistence—and the social structure that governs it—shapes the welfare

consequences of temporary, highly visible interventions.

Figure 6 summarises cumulative welfare under alternative persistence scenarios constructed using the estimated decay process. All counterfactuals hold fixed the contemporaneous treatment effect and differ only in the rate at which compliance attenuates after visible reinforcement ends. Welfare is lowest in the absence of any intervention and rises monotonically with post-intervention persistence. A purely contemporaneous response with no persistence generates limited cumulative gains despite a large short-run effect. Faster decay substantially attenuates welfare relative to the observed intervention, while slower decay yields markedly larger gains. The observed intervention lies strictly between these benchmarks, indicating that while persistence contributes meaningfully to welfare, a substantial share of potential gains is lost to post-intervention decay. These patterns reinforce a central implication of the framework: welfare depends on the area under the compliance path rather than on peak adoption alone.

Interpreted through the lens of the coordination framework developed in Section 3, the slower-decay counterfactual corresponds to a more cohesive social environment in which beliefs about peer compliance erode gradually, whereas faster decay captures settings with weaker coordination and more rapid belief unraveling. The welfare ranking therefore maps directly into the heterogeneity results. Identical visible interventions can generate similar contemporaneous responses across communities, yet produce sharply different cumulative benefits depending on local social structure. In low-cohesion environments, behaviour decays quickly once visibility fades, limiting the welfare returns to temporary reinforcement. In cohesive communities, endogenous reinforcement sustains compliance beyond the active period, amplifying cumulative gains even when policy effort is short-lived.

These findings have direct implications for policy design. Extending the duration or intensity of visible reinforcement mechanically raises contemporaneous compliance, but yields diminishing welfare returns when decay is rapid. In such settings, additional pol-

icy effort primarily shifts behaviour while reinforcement is active, with little persistence once it ends. By contrast, when social interactions support coordination, short, salient intervention pulses can generate substantial welfare gains without permanent enforcement. Visibility can therefore substitute for sustained monitoring only under specific social conditions. From a design perspective, targeting visibility-based policies toward environments where decay is likely to be slow may be more effective than uniformly extending intervention duration.

Two caveats are worth emphasising. First, the welfare counterfactuals abstract from general-equilibrium spillovers across neighbourhoods and from longer-run adjustments in compliance rules or expectations beyond the study horizon. Second, the decay parameter is interpreted as a reduced-form summary of equilibrium behavioural erosion under declining observability, not as a deep preference or habit parameter. The results should therefore be read as guidance for comparative policy design rather than prescriptions for optimal intervention. Within these bounds, the analysis clarifies a key lesson: policies that maximise peak compliance need not maximise welfare, and the persistence of behaviour—shaped by social structure—is a first-order determinant of policy effectiveness.

9 Conclusion

This paper studies how compliance with welfare-enhancing non-market input adoption rules evolves when policy relies on temporary, highly visible interventions rather than sustained enforcement. The central message is simple but consequential: visibility is powerful, yet fragile. Highly visible reinforcement can generate large and rapid behavioural responses, even in dense urban environments with weak enforcement capacity. However, these gains are not inherently durable. Once visible cues are withdrawn, compliance attenuates, and the speed of this decay depends critically on local social structure.

A key contribution of the paper is to shift attention away from peak adoption toward the dynamics of persistence and decay. Much of the existing evidence on visibility-based or salience-based policies focuses on contemporaneous treatment effects. While such effects are often substantial, they provide an incomplete basis for evaluating policy effectiveness. Behavioural change that unravels quickly after intervention ends may deliver limited cumulative benefits, even if short-run responses appear impressive. By explicitly tracing post-intervention dynamics, this paper shows that the welfare consequences of visible policy depend not only on how strongly behaviour responds, but on how long those responses endure.

The empirical results highlight that dense urban environments are not homogeneous in their capacity to sustain behavioural change. Communities with higher social cohesion exhibit markedly slower post-intervention decay despite responding similarly during the active intervention period. This pattern is difficult to reconcile with explanations based on information provision, habit formation, or permanent preference change. Instead, it supports an interpretation in which visible reinforcement temporarily coordinates beliefs about others' behaviour, and persistence reflects endogenous reinforcement through repeated social interaction. Where cohesion is high, shared reference points and repeated encounters sustain expectations of peer compliance even after external cues fade. Where cohesion is weak, beliefs unravel quickly and compliance reverts toward baseline.

This distinction has important implications for how visibility-based policies should be interpreted. Temporary persistence should not be taken as evidence of durable compliance internalisation. Nor should rapid decay be viewed as policy failure. In the framework developed here, decay is an equilibrium outcome under declining observability, not a behavioural anomaly. Visible interventions shift behaviour by altering perceived social incentives, but these incentives depend on continued observability. When observability declines, so does the social-utility component of compliance. The relevant question for policy is therefore not whether decay occurs, but where and how quickly it does so.

The welfare analysis underscores this point. Policies that maximise peak compliance need not maximise welfare if behavioural gains decay rapidly once reinforcement ends. Extending the duration of visible reinforcement can increase contemporaneous compliance, but it also incurs additional costs and yields diminishing returns in settings where social structure cannot sustain coordination. In contrast, short, salient interventions can generate substantial welfare gains when targeted toward cohesive communities, where endogenous reinforcement slows decay and amplifies cumulative benefits. These results suggest that optimal policy design depends not only on the intensity or duration of intervention, but critically on where decay is likely to be slow.

More broadly, the findings imply that social structure is a first-order determinant of the dynamic effectiveness of public policy. Visibility can substitute for enforcement only under specific conditions. In environments where local networks reinforce expectations, temporary public cues can catalyse collective action at low cost. Where such reinforcement is absent, identical interventions may generate large but fleeting responses. Treating social structure as a mere moderator of treatment effects understates its role; instead, it shapes the entire dynamic path of behavioural change.

The analysis also speaks to the design of scalable policy in low-capacity settings. Enforcement-intensive approaches are often infeasible in dense cities with limited administrative resources. Visibility-based interventions offer an appealing alternative precisely because they leverage existing public spaces and social interactions. However, the results here caution against assuming that such interventions are universally effective or self-sustaining. Effective design requires identifying environments where visibility is likely to generate endogenous reinforcement rather than rapid decay. This perspective shifts the policy question from how much reinforcement to provide to where and when to provide it.

Several broader implications follow. First, dynamic evaluation should become standard in the study of behavioural policy. Short-run treatment effects are insufficient to assess

welfare or cost-effectiveness when behaviour evolves endogenously after intervention ends. Second, heterogeneity in persistence deserves as much attention as heterogeneity in impact. Communities that look similar in terms of contemporaneous response may differ substantially in their capacity to sustain behavioural change. Third, the results suggest that urban density alone is not a reliable predictor of policy effectiveness. Density can amplify visibility, but without cohesive social interaction it may also accelerate decay.

The framework and evidence presented here have limitations that point to directions for future research. The analysis focuses on a specific class of non-market input behaviours that are weakly enforceable and socially observable. Other behaviours may exhibit different dynamics, particularly when private benefits are small or social visibility is limited. In addition, the welfare counterfactuals are partial equilibrium and abstract from potential general-equilibrium spillovers across neighbourhoods or longer-run adjustments in compliance. Understanding how repeated interventions interact over longer horizons remains an important open question.

Despite these limitations, the paper offers a clear lesson: visibility is not a substitute for enforcement by default, but it can be an effective substitute under the right social conditions. Temporary, highly visible interventions can catalyse collective compliance at low cost, but their success hinges on whether local social structure sustains coordination once reinforcement fades. Designing effective policy therefore requires understanding not only how people respond to visible cues, but how their expectations evolve when those cues disappear.

In settings where enforcement capacity is limited and behavioural change is urgently needed, this distinction is crucial. By clarifying when visibility-based policies generate durable benefits and when decay dominates, this paper provides a framework for designing interventions that are not only impactful, but dynamically effective.

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Appendix

A. Supplementary Tables and Figures

Table A1: Treatment Effects on Proper Mask Wearing by Location Type (Appendix)

	Markets (1)	Mosques (2)	Pooled (3)
Treatment	3.680**	6.684**	4.477**
	(1.560)	(2.464)	(1.669)
Baseline proper mask share (market)	0.524***		
	(0.080)		
Baseline proper mask share (mosque)		0.682***	
		(0.108)	
Baseline proper mask share (overall)			0.479***
			(0.087)
Strata fixed effects		Yes	
Constant	8.008**	7.435*	10.507**
	(3.811)	(3.558)	(4.163)
Observations (N)	30	30	30

Notes: Each column reports a separate regression at the subdivision level. The dependent variable is the share of individuals observed wearing masks properly. Treatment is an indicator for assignment to the salience intervention. Columns (1) and (2) restrict the sample to observations from markets and mosques, respectively; column (3) pools all locations. All specifications include strata fixed effects and control for baseline proper mask usage at the relevant location level. Robust standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A2: Difference-in-Differences Estimates by Location Type

	Markets (1)	Mosques (2)
Treatment × Active	0.131***	0.053**
	(0.035)	(0.020)
Treatment × After	0.174***	0.042*
	(0.061)	(0.024)
Subdivision FE	Yes	Yes
Week FE	Yes	Yes
Observations (N)	297	297

Notes: Each column reports a separate difference-in-differences specification estimated using `reghdfe`. The dependent variable is the share of individuals observed wearing masks properly at the subdivision–week–location level. Treatment × Active captures the contemporaneous effect during the intervention period, while Treatment × After captures post-intervention persistence. All specifications include subdivision and week fixed effects. Standard errors are clustered at the subdivision level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A3: Cohesion, Partial Persistence, and Reduced-Form Decay

	(1) FE	(2) FE × Cohesion	(3) Weekly FE Event Study	(4) Reduced-Form Decay
Panel A: Reduced-form treatment effects				
Treatment × Active	0.092***	0.090**		
	(0.023)	(0.040)		
Treatment × After	0.108***	0.059		
	(0.035)	(0.044)		
Treatment × Active × High_{coh}		0.008		
		(0.047)		
Treatment × After × High_{coh}		0.120*		
		(0.067)		
Panel B: Event-study dynamics				
Week FE × Treatment			Yes	
Panel C: Reduced-Form Decay				
Initial post-period effect (A)				0.176
				(0.633)
Decay rate (λ)				1.774
				(3.573)
Subdivision FE	Yes	Yes	Yes	Yes
Week FE	No	No	Yes	No
Observations (N)	594	594	594	594

Notes: The dependent variable is the share of individuals observed wearing masks properly at the subdivision–week–location level. Columns (1) and (2) estimate reduced-form difference-in-differences specifications with fixed effects for pre-defined time windows. Column (2) allows treatment effects to vary by a high-cohesion indicator. Column (3) reports a fully saturated event-study specification with week fixed effects interacted with treatment. Column (4) estimates a nonlinear exponential decay model of post-intervention dynamics, where A captures the initial post-period effect and λ governs the rate of decay.

While contemporaneous treatment effects are similar across cohesion levels, post-intervention persistence is relatively stronger in more cohesive subdivisions, consistent with slower decay in belief-driven compliance.

Cohesion is measured as the negative absolute difference between market and mosque compliance during baseline weeks (1–2). Active weeks are weeks 3–8; after weeks are weeks 9–10. Standard errors are clustered at the subdivision level. Estimates of λ rely on only two post-intervention weeks and should be interpreted with caution. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Illustrative comparison of programme cost and effect size across urban and rural settings

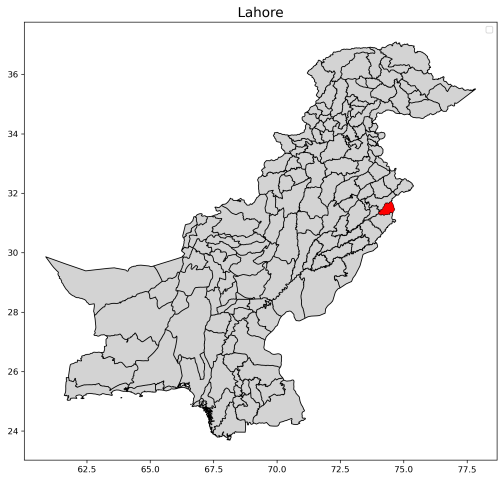
Study / Setting	Effect (pp)	Total cost (USD)	Cost per adopter (USD)
This study (urban Lahore)	4.47	52,629	1.86
Benchmark study (rural setting)	29.00	327,447	9.49

Notes: This table provides an illustrative comparison of programme costs and effect sizes across urban and rural compliance interventions. The urban estimates correspond to the bundled access and salience intervention studied in this paper and report the average increase in proper compliance during the active intervention period. The rural benchmark is drawn from a large-scale field experiment conducted in a low-density setting and reports the corresponding increase in compliance during the intervention window. Programme costs include implementation and delivery expenditures but exclude research, monitoring, and evaluation costs in both cases. Effect sizes, populations, baseline compliance rates, and intervention designs differ across studies; as such, the comparison is not intended to represent a welfare ranking or a causal estimate of relative efficiency, but rather to illustrate how population density and network structure may affect the cost scale of behaviour-change interventions.

Table A5: Ancillary outcome (placebo): effect on electricity line losses

	(1)
Treatment (bundled programme)	0.013
	(0.178)
Observations (clusters)	30
Strata fixed effects	Yes
Week fixed effects	Yes

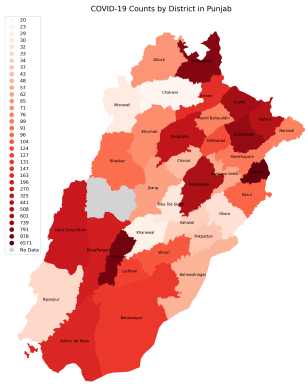
Notes: This table reports the effect of the bundled access and salience intervention on an ancillary outcome—technical electricity line losses—used as a placebo test for broader behavioural or enforcement spillovers. The dependent variable is a normalised index of weekly technical line losses at the subdivision level over the study window. Line losses are a salient non-market input outcome in the same administrative units but are not directly targeted by the intervention and are unlikely to respond to short-run changes in health-related adoption rules or visibility cues. The estimated coefficient is small in magnitude and statistically indistinguishable from zero, consistent with the intervention operating through behaviour-specific salience and observability rather than through generalised compliance, enforcement, or monitoring effects. Standard errors are clustered at the subdivision (cluster) level.



(a) Lahore within Pakistan



(b) Lahore District boundary



(c) COVID-19 incidence across Punjab

Figure A1: Geographic context of the study setting. Panel (A) locates Lahore within Pakistan. Panel (B) shows the administrative boundary of Lahore District, within which the experimental clusters were situated. Panel (C) displays relative COVID-19 case incidence across Punjab districts prior to the intervention period. The maps are provided for geographic orientation only and do not enter the empirical analysis.

B. Robustness and Sensitivity Analyses

This subsection presents robustness and sensitivity analyses that support the identification and interpretation of the main results. The checks assess robustness to alternative fixed-effects structures, definitions of the post-intervention period, and the influence of individual time periods. Together, these exercises show that the estimated treatment effects and post-intervention persistence are not driven by specific modelling choices or by any single week of data.

Overview of robustness checks in this section:

- *Fixed effects structure:* Alternative specifications using subdivision fixed effects only and subdivision plus week fixed effects.
- *Inference procedures:* Heteroskedasticity-robust standard errors as a complement to clustered inference.
- *Post-intervention timing:* Alternative definitions of the post-intervention period, including exclusion of the immediate post week.
- *Influential periods:* Leave-one-week-out sensitivity analysis of the post-intervention treatment effect.

Table B1: Alternative Fixed Effects Specification: Subdivision FE Only

	(1) Proper mask share
Treatment × Active	0.091***
	(4.03)
Treatment × After	0.107**
	(3.13)
Subdivision FE	Yes
Week FE	No
Observations (N)	596

Notes: This table reports difference-in-differences estimates using subdivision fixed effects only. The dependent variable is the share of individuals observed wearing masks properly. Treatment × Active captures the contemporaneous effect during the intervention period, while Treatment × After captures post-intervention persistence. t-statistics are reported in parentheses. Standard errors are clustered at the subdivision level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B2: Alternative Fixed Effects Specification: Subdivision and Week FE (Baseline)

	(1) Proper mask share
Treatment × Active	0.092***
	(4.01)
Treatment × After	0.108**
	(3.12)
Subdivision FE	Yes
Week FE	Yes
Observations (N)	594

Notes: This table reports difference-in-differences estimates using subdivision and calendar week fixed effects. The dependent variable is the share of individuals observed wearing masks properly. Treatment × Active captures the contemporaneous effect during the intervention period, while Treatment × After captures post-intervention persistence. t-statistics are reported in parentheses. Standard errors are clustered at the subdivision level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B3: Inference Robustness Using Heteroskedasticity-Robust Standard Errors

	(1) Proper mask share
Treatment × Active	0.092***
	(4.56)
Treatment × After	0.108***
	(3.91)
Subdivision FE	Yes
Week FE	Yes
Observations (N)	594

Notes: This table reports the baseline difference-in-differences specification estimated using heteroskedasticity-robust standard errors rather than clustered standard errors. The dependent variable is the share of individuals observed wearing masks properly. t-statistics are reported in parentheses. All specifications include subdivision and week fixed effects. Results are quantitatively similar to the clustered standard error specification. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



Figure B1: Leave-One-Week-Out Sensitivity of Post-Intervention Treatment Effect

Notes: This figure reports estimates of the post-intervention treatment effect (Treatment × After) obtained by iteratively re-estimating the baseline difference-in-differences specification while omitting one calendar week at a time. The horizontal axis indicates the dropped week. Points denote point estimates, and vertical bars represent 95% confidence intervals based on standard errors clustered at the subdivision level. The dashed horizontal line marks zero. Estimates are stable across dropped weeks, indicating that post-intervention persistence is not driven by any single week. Figure C4 shows that the estimated post-intervention treatment effect is stable across leave-one-week-out re-estimations. Omitting the final post-intervention week increases the estimated effect, consistent with that week exhibiting the greatest attenuation of compliance. The increase in the estimated effect when the final week is omitted reflects the fact that attenuation is strongest at longer horizons, consistent with gradual decay in post-intervention compliance.

Table B4: Alternative Definition of the Post-Intervention Period: Excluding the Immediate Post Week

	(1) Proper mask share
Treatment × Active	0.048**
	(2.78)
Treatment × After (Long window)	0.039
	(1.57)
Subdivision FE	Yes
Week FE	Yes
Observations (N)	594

Notes: This table reports difference-in-differences estimates using an alternative definition of the post-intervention period that excludes the first week following the end of active reinforcement. The dependent variable is the share of individuals observed wearing masks properly. Treatment × Active captures the contemporaneous effect during the intervention period, while Treatment × After (Long window) captures persistence beginning two weeks after reinforcement ends. t-statistics are reported in parentheses. All specifications include subdivision and week fixed effects, and standard errors are clustered at the subdivision level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C. Data, Replication, and Implementation Notes

All analysis was conducted in Stata 17 using code scripts provided in the replication package. Microdata cannot be publicly released under the terms of the administrative agreement, but replication materials sufficient to reproduce all tables and figures—including generated cluster-level aggregates and analysis code are archived with the journal upon publication. Implementation of treatments and data collection were supervised directly by my research team as well as the hired survey firm. All code for data cleaning, estimation, and figure production will be made available through the *Review of Economics and Statistics* replication repository.

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