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Digital Investment and the Evolution of Government Services*

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Abstract

This paper examines whether public investments in digital infrastructure improve citizen-facing government performance. We combine administrative data on the staggered rollout of a large-scale digitalization program with high-frequency social-media data for Italian municipalities, using online communication as a proxy for public service delivery. Exploiting variation in treatment timing, we estimate causal effects across access, usage, and outcomes. Digital investments increase municipalities' online presence and communication activity: treated municipalities are more likely to adopt social media, post more frequently, and generate higher aggregate engagement. However, improvements in effectiveness are limited in the short run. Engagement per post remains unchanged, and gains in communication quality, measured by readability, emerge only gradually. These findings suggest that while digital investments expand activity, translating them into effective communication requires time and complementary capabilities.

Keywords: Digital transformation; Structural change; Public sector digitalization; Technological adoption; Digital divide; Government communication; High-frequency data.

JEL Classification: O33; O38; H75; C23.

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1 Introduction

A defining feature of the digital age is the ability to observe policy outcomes with unprecedented timeliness and granularity, beyond what traditional administrative data allow. High-frequency digital traces—from card transactions to satellite imagery to social-media feeds—have already transformed measurement in domains such as macroeconomic monitoring and environmental enforcement (Einav and Levin, 2014; Varian, 2014; Resce and Maynard, 2018; Chetty *et al.*, 2024). At the same time, governments are investing heavily in the digital transformation of public administration, raising a fundamental question: do these investments improve citizen-facing outcomes (Yang *et al.*, 2024; Greavu-Şerban *et al.*, 2025)?

This paper answers this question by combining digital trace data with administrative records on public digital investments. We study the causal impact of digitalization funding on public communication using high-frequency social-media data from Italian municipalities. Our empirical setting is the staggered rollout of the *PA digitale 2026* program, a large-scale policy that funds digital infrastructure and platforms in local governments, generating quasi-experimental variation in treatment timing.

We measure results using official social-media activity of municipalities, which provides a scalable proxy for citizen-facing communication. To interpret these effects, we adopt the multi-level digital divide framework, which distinguishes between inequalities in access, use, and outcomes (Hargittai, 2002; van Dijk, 2005; Scheerder *et al.*, 2017; Mazzoni *et al.*, 2024). Although developed for individuals, this framework applies naturally to public institutions: municipalities may differ in whether they are online (first-level divide), in how intensively and in what way they use digital tools (second-level divide), and whether digital activity translates into meaningful outcomes such as transparency, service quality, and citizen inclusion (third-level divide) (Scheerder *et al.*, 2017). Guided by this framework, we examine whether digitalization funding affects (i) social-media adoption (van Dijk, 2005), (ii) posting activity, content composition, and total engagement (Hargittai, 2002), and (iii) per-post resonance and communication quality, measured using the Gulpease index (Lucisano *et al.*, 1988). Identification relies on staggered treatment timing, and we implement Difference-in-Differences estimators that are robust to heterogeneous effects (Callaway and Sant'Anna, 2021; Baker *et al.*, 2025), complemented by event-study designs.

Italy provides a suitable setting. Before the pandemic, it ranked 15^{th} in the OECD Digital Government Index (OECD, 2020) and 19^{th} in the EU Digital Public Services Index (European Commission, 2020), reflecting substantial heterogeneity in local digital capacity. The COVID-19 crisis accelerated digitalization (Cati, 2024), and the National Recovery and Resilience Plan (NRRP) introduced *PA digitale 2026*, a €6.74 billion program. Because funding is allocated through sequential calls, municipalities enter treatment at different times, enabling a staggered identification strategy (Roth *et al.*, 2023). Despite its scale, there is little evidence that such investments improve the way governments communicate with citizens.

Existing work on municipal digitalization focuses on technology adoption and administrative efficiency (Arduini *et al.*, 2010, 2013; Attour and Chaupain-Guillot, 2020; Duygan *et al.*, 2023), while evidence on citizen-facing outcomes remains limited. NRRP studies examine participation patterns (De Pascale *et al.*, 2024), but do not assess downstream effects. More broadly, while digital trace data are increasingly used for policy measurement (Blazquez and Domenech, 2018; Abbasiharofteh *et al.*, 2023; Rammer and Es-Sadki, 2023), there is little causal evidence linking digitalization subsidies to changes in public communication, and none that maps these effects across different levels of the digital divide.

We find that digitalization subsidies have heterogeneous effects across these dimensions. At the first level, funding increases the probability that municipalities adopt social media networks. At the second level, treated municipalities post more and generate greater total engagement, with effects that grow over time and reflect a shift toward more information-based text-based communication. At the third level, effects are limited: the rate of engagement per post does not increase, and improvements in communication quality emerge only gradually. These results indicate that digital investment expands access and activity but does not immediately translate into more effective communication.

The paper makes two contributions. First, it provides causal evidence on the digital divide in public institutions, showing that the distinction between access, usage, and outcomes extends to local governments. Second, it demonstrates that social-media data can be used as high-frequency outcome measures for policy evaluation, helping to shorten the feedback loop between policy implementation and measurement (Schneeweiss *et al.*, 2015; Tillmann *et al.*, 2025), and complementing recent evaluations of place-based policies based on administrative data (Atella *et al.*, 2023; Monturano *et al.*, 2025).

The remainder of the paper is organized as follows. Section 2 provides background information. Section 3 describes the data and the empirical strategy. Section 4 presents the results. Section 5 concludes.

2 Background

2.1 Digital traces and near-real-time policy evaluation

A growing body of literature shows that digital traces can substantially reduce the time lag between policy implementation and the measurement of outcomes. This data revolution in economics is characterized by the availability of large-scale and high-frequency data that has opened new possibilities for monitoring and evaluating public interventions (Einav and Levin, 2014; Varian, 2014; Giest, 2017).

During the COVID-19 crisis, researchers built high-frequency economic indicators from private-sector data to track activity in near real time and to evaluate stabilization policies while they were still unfolding (Chetty *et al.*, 2024). High-resolution payment and card-transaction data have been used to validate digital proxies for consumption and to separate the effects of containment policies from economic support measures (Carvalho *et al.*, 2021; Cevik, 2022). Mobility traces derived from mobile devices have enabled timely evaluations of non-pharmaceutical interventions by linking policy timing to behavioral responses and health outcomes (Gao *et al.*, 2020; Murray, 2021; Xu, 2021). More recently, mobile phone data have been utilized to evaluate urban transport infrastructure, illustrating the transformative potential of passively collected digital data for causal policy analysis (Lutz *et al.*, 2025). In other domains, satellite-based systems provide continuous monitoring that supports the implementation and evaluation of environmental policies, while technical limits of the monitoring technology itself can influence both behavior and measured impacts (Mullan *et al.*, 2022; Baragwanath and Shinde, 2025). Methodologically, this has prompted research on how to integrate unstructured digital data into causal inference to proxy otherwise unobservable confounders (Jerzak *et al.*, 2023).

A parallel strand of work exploits web-generated data for broader economic measurement. Google search volumes have been used to "predict the present" for macroeconomic indicators (Choi and Varian, 2012; Eichenauer *et al.*, 2022), and Italy's statistical office has explored social-media sentiment as a near-real-time economic gauge (ISTAT, 2024). Web-scraped data have been used to construct innovative indicators of innovation and socio-economic development (Resce and Maynard, 2018; Kinne and Lenz, 2021; Carneiro *et al.*, 2022b,a; Ashouri *et al.*, 2024; Bottai *et al.*, 2024) to measure the corporate digital divide (Mazzoni *et al.*, 2024) and to monitor e-commerce adoption (Blazquez *et al.*, 2019). Rammer and Es-Sadki (2023) provide a comprehensive review of big-data approaches to measure innovation at firm-level, while Abbasiharofteh *et al.* (2023) propose a "digital layer" as a complementary data source for regional and innovation studies.

2.2 The multi-level digital divide in public administration

The concept of a digital divide has evolved from a binary distinction between "haves" and "have-nots" into a multi-layered framework. van Dijk (2005) distinguishes access divides (physical availability of technology), skills divides (the ability to use technology effectively), and usage divides (the breadth and depth of actual use). Hargittai (2002) formalized the notion of a "second-level digital divide," shifting attention from connectivity to competence, while Scheerder *et al.* (2017) extended the framework to outcomes, whether digital engagement translates into tangible benefits. Most empirical applications focus on individuals and households (Norris, 2001; van Deursen and van Dijk, 2014), but the framework is equally relevant to organizations, and especially to local governments. At the organizational level, Mergel *et al.* (2019) conceptualize digital transformation in the public sector as encompassing not only technology adoption, but also changes in organizational culture and service delivery, a process that naturally maps onto the multi-level divide. Municipalities differ enormously in their digital readiness (Holzer and Kim, 2003; Duygan *et al.*, 2023), and previous work has documented persistent digital divides in e-government service provision that mirror inequalities in administrative capacity, fiscal resources, and geographic remoteness (Mossberger *et al.*, 2003; Blank *et al.*, 2018). Efficiency-oriented local governments tend to adopt digital innovations earlier and more broadly (Jun and Weare, 2011), and strong technological and political capabilities are essential for the effective planning and implementation of e-government (Gallego-Álvarez *et al.*, 2010). The diffusion of e-government across municipalities also exhibits spatial interdependence, as neighboring jurisdictions influence each other's digital initiatives through learning, competition, and legitimacy-seeking behavior (Wang and Jayakar, 2024; Hong *et al.*, 2022). Beyond efficiency gains, digitalization is also expected to enhance transparency and accountability, ultimately strengthening public trust in political and bureaucratic institutions (Twizeyimana and Andersson, 2019). It also has the potential to stimulate civic engagement (Dimitrova *et al.*, 2014; Kruikemeier *et al.*, 2014), increase citizen participation in the political process (Pristl and Billert, 2022), and promote greater inclusiveness in civil society (Goldfinch *et al.*, 2009). These broader democratic benefits depend, however, not only on whether municipalities "are online", but on the quality and accessibility of the content they produce, a distinction that maps directly onto the third level of the digital divide.

2.3 Municipal digital capacity and civic communication

Within this broader agenda, *PA digitale 2026* can be viewed as a place-based policy intervention aimed at increasing municipal digital capacity through targeted funding (Barca, 2019; Fratesi, 2025). The program targets the same local administrations that previous research has identified as critical nodes for public-service delivery and digital innovation (Gonzalez *et al.*, 2013; Eneqvist, 2023), yet whose readiness for digital adoption varies widely (Holzer and Kim, 2003; Duygan *et al.*, 2023), and whose capacity to attract and absorb policy funds is itself heterogeneous (Di Stefano and Resce, 2025).

While many methods for evaluating digitalization focus on technology adoption or administrative efficiency (Arduini *et al.*, 2010, 2013; Attour and Chaupain-Guillot, 2020), citizen-facing outcomes are essential for assessing whether digital transformation improves public value (Twizeyimana and Andersson, 2019). Empirical evidence from Italian municipalities confirms that the development and intensity of e-government services depend heavily on context-specific factors such as local productive structure, infrastructure endowments, and neighboring adoption patterns (Arduini *et al.*, 2010, 2013). International evidence further documents that municipal e-government diffusion has progressed unevenly over the past two decades, both within and across countries (Budding *et al.*, 2018; Cepparulo and Zanfei, 2021; Epstein, 2022; Caravaggio *et al.*, 2025). A growing body of work examines how governments use social media platforms for communication, participation, and self-presentation (Criado *et al.*, 2013; Medaglia and Zheng, 2017), yet causal evidence on whether subsidies improve these outcomes remains scarce. Social media platforms provide a particularly suitable measurement channel: municipalities can communicate directly with residents and citizens can respond immediately, generating granular behavioral outcomes that are difficult to observe in administrative data alone (Mergel and Bretschneider, 2013; Guillamón *et al.*, 2016; Faber *et al.*, 2020). Moreover, the type of content that local governments produce online, whether text-based and informational or visual and engagement-oriented, is itself a dimension of digital capacity that varies across municipalities (Bonsón *et al.*, 2015; Haro-de Rosario *et al.*, 2018), yet this has not been examined in the context of digitalization subsidies.

Importantly, programs such as *PA digitale 2026* typically do not directly fund social-media communication. The available calls for tender usually target specific infrastructure upgrades such as cloud migration, digital identity integration (*SPID* and *CIE*[1]), interoperability among public administrations, the digitalization of public notices, and the development of digital payment systems for services, taxes, and fees. Any effect on social-media activity therefore, operates through indirect channels: the program may lead to hiring or retraining of digital staff who also manage institutional communication, it may trigger broader organizational attention to online presence, or the modernized infrastructure may lower the cost of producing and sharing digital content. Understanding that the causal pathway is indirect is important for interpreting the results, as it implies that the program reshapes institutional digital capacity in ways that spill over into citizen-facing communication rather than targeting it directly.

3 Data and Methodology

3.1 Sample construction and treatment definition

As of 2025, Italy comprises 7,904 municipalities. For our analysis we checked whether each of these municipalities operates an official Facebook and/or Instagram page and we constructed a municipality-year panel for the period 2009–2025, covering both pre- and post-intervention periods. Of the 7,904 municipalities, 4,493 (56.9%) maintained at least one active social-media page as of 2025. Treatment is defined by using administrative funding records published on the *PA digitale 2026* open-data repository.[2] The program operates through sequential calls, each targeting a specific NRRP measure. Municipalities self-

[1]SPID (*Sistema Pubblico di Identità Digitale*) is Italy's public digital identity system that allows citizens to access online public and private services with a single set of credentials. CIE (*Carta d'Identità Elettronica*) is the electronic identity card issued by the Italian government, which also enables secure authentication for digital services.

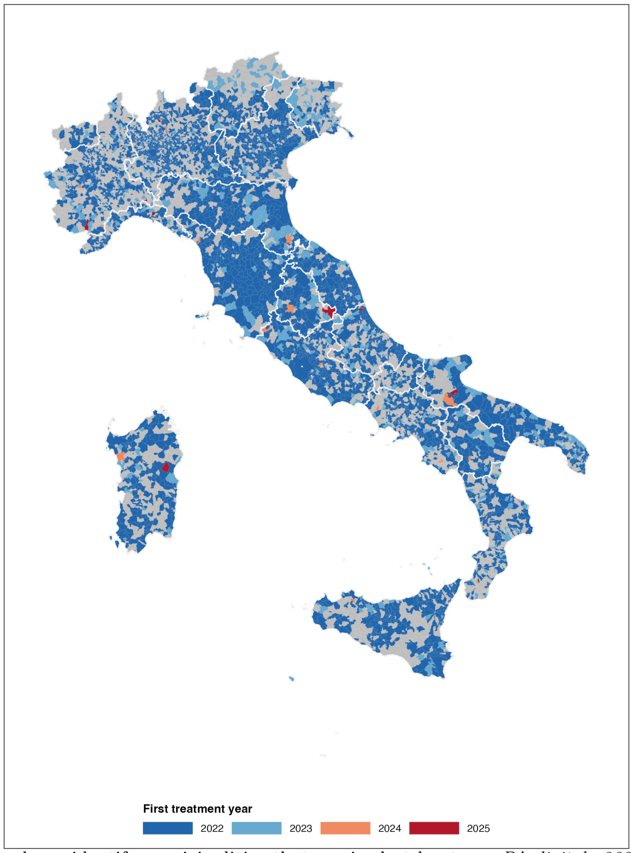
[2]Available at the following GitHub link.

select in relation to participation, and applications are subject to automatic eligibility checks performed by the platform and are processed in chronological order of submission; there is no merit-based evaluation or competitive scoring. A municipality is treated as starting in the first year in which it receives a positive financing decree. Because calls open at different dates and municipalities apply at different times, entry into treatment is staggered across both cohorts and calendar years. Some municipalities remain untreated for part of the observation window, providing not-yet-treated comparators, while others never receive funding and thus constitute the never-treated group.

Figure 1 maps the treatment status of Italian municipalities based on year of treatment. The program reaches municipalities across all macro-regions, although visual inspection suggests denser coverage in Centre and South Italy, consistent with the NRRP's emphasis on territorial cohesion and digital catch-up. Grey areas indicate municipalities without an official social-media page in our sample.[3]

[3]We checked for the presence of official social media pages at the end of June 2025. We first examined municipalities' official websites to identify linked public profiles, and then conducted a manual search. Regarding Facebook, only 51.7% of municipalities shared their official account on their websites; however, with manual identification, this share increased to 77.1%. For Instagram, the percentages were lower: only 16.2% of municipalities reported their official account on their websites, while manual identification raised this figure to 40.3%. Notably, although we were able to identify official Facebook accounts for nearly four-fifths of municipalities, some of these accounts were found to be empty.

Figure 1: *Treatment status of Italian municipalities under PA digitale 2026*



Notes: Different colours identify municipalities that received at least one *PA digitale 2026* digitalisation subsidy, grouped by cohort of first treatment. Grey areas denote municipalities without a detected social-media page.
Sources: Authors' elaboration based on *PA digitale 2026* administrative records and ISTAT municipal boundaries (ISTAT, 2025).

3.2 Social-media outcomes

We collect post-level data from official municipal social-media pages (Facebook and Instagram) via web scraping (Bottai *et al.*, 2024). While the raw data are timestamped at high frequency, we aggregate to the municipality-year level to align with the annual treatment definition and to reduce noise from short-lived platform shocks. Our outcome matrix is organised around three dimensions of the municipal digital divide: (i) social media adoption, (ii) communication intensity and citizen engagement, and (iii) content quality and composition.

Adoption: Social-media adoption is measured as a binary indicator equal to one from the first year in which the municipality publishes at least one post on an official page (Faber *et al.*, 2020; Guillamón *et al.*, 2016; Faber, 2022; Mabillard *et al.*, 2024). This is consistent with the three-stage model of Mergel and Bretschneider (2013), in which the initial decision to establish an institutional social-media presence constitutes a discrete, observable threshold.

Communication intensity: The primary measure is the *number of posts* published by the municipality in year t. Posting frequency is a standard proxy for institutional online activity and has been shown to vary systematically with organizational capacity and local-government characteristics (Guillamón *et al.*, 2016; Faber *et al.*, 2020). We complement the aggregate post count with two content-specific counts: the number of posts containing at least one *hyperlink* and the number containing at least one *image*, which capture different modes of institutional communication (Bonsón *et al.*, 2015; Haro-de Rosario *et al.*, 2018). Link presence is detected by matching on the textual content of each post (Carneiro *et al.*, 2025) (*i.e.*, matching URLs beginning with `http://`, `https://`, or `www.`). Image presence is inferred from platform metadata: all Instagram posts are classified as image posts by construction, while Facebook posts are flagged as containing an image when the scraped record includes a non-empty image-related field (*e.g.*, photo URL, media type, or thumbnail). These content-type indicators allow us to decompose the overall posting effect into its textual and visual components, shedding light on the *type* of digital communication that the program stimulates.

Citizen engagement: We measure total *engagement* as the sum of likes and comments received on a municipality's posts in year t, aggregated to the municipality-year level. Previous work demonstrates that engagement metrics capture meaningful citizen responses to local-government communication and are sensitive to content type and media strategy (Mergel and Bretschneider, 2013; Bonsón *et al.*, 2015). To disentangle the role of posting volume from per-post resonance, we also compute *engagement per post* as the ratio of total engagement to the number of posts in a given municipality-year.

Content quality and composition: We capture communication quality through the Gulpease readability index, a metric specifically tailored to the

Italian language that summarises text complexity on a 0–100 scale, where higher values indicate easier-to-read content (Lucisano *et al.*, 1988).[4] Readability indices have been applied to evaluate the accessibility of institutional language in contexts ranging from university reporting and central-bank communication to regulatory texts and political discourse (Allini *et al.*, 2017; Ferrara and Angino, 2022; Alfano and Guarino, 2024; Blinder *et al.*, 2024). Readability is undefined when no textual content is posted; therefore, municipality-year cells with zero posts are excluded from the readability analysis to avoid mechanically assigning scores to missing communication.[5]

The count outcomes (posts, engagement, posts with links, and posts with images) are non-negative and heavily right-skewed, with a substantial mass at zero in the full panel.[6] In such settings estimates on untransformed counts would be dominated by a small number of high-activity municipalities, and the resulting average treatment effects would be difficult to interpret substantively. Therefore, as our preferred specification, we apply the inverse hyperbolic sine (IHS) transformation:

$$\text{asinh}(y) = \ln\left(y + \sqrt{y^2 + 1}\right) \tag{1}$$

which is defined at $y = 0$, preserves zero-valued observations, and behaves like a log transformation for large values. The IHS has a long tradition in regression models for skewed outcomes (Burbidge *et al.*, 1988; Bellemare and Wichman, 2020). As Chen and Roth (2024) show, Average Treatment on the Treated (ATT) estimates under log-like transformations are sensitive to the units of the outcome when the treatment affects the extensive margin. This concern is mitigated in our setting because all count outcomes are naturally expressed as integers, making the unit of measurement unambiguous, and we report results under both $\text{asinh}(y)$ and $\ln(y)$ (Bellégo *et al.*, 2022) as a robustness check. Share outcomes and the Gulpease index are analysed by levels.

[4]More detail on the Gulpease index is reported in the Appendix A.1.

[5]The share outcomes are similarly undefined for municipality-years with zero posts and are set to zero in such cases, following standard practice.

[6]See Table A1.

3.3 Descriptive statistics

To characterize the cross-sectional variation in social-media activity at the end of the observation window, Table 1 reports summary statistics for 2025, the year that reflects the most complete post-treatment landscape.[7] Values describe the 4,493 municipalities (56.9% of all Italian municipalities as of 2025) that maintained at least one active social-media page, capturing only actively communicating administrations.

Panel A reports outcome variables in levels with median values for municipalities of 131 posts over the year and roughly 15 interactions per post, for a total of about 1,955 engagement actions (likes plus comments). Even within this active subset, distributions are heavily right-skewed: the standard deviation of the post count exceeds its mean by more than an order of magnitude, motivating the log-like transformations reported in Panel B. The median Gulpease score is 54.9 points, just below the 60-point threshold typically associated with middle-school readability, consistent with content that remains linguistically demanding for many citizens. Regarding content composition, the median municipality published 11 posts containing a hyperlink and 10 containing an image; the share of posts with links (median 9.1%) and images (median 9.0%) are similar in magnitude but highly dispersed, reflecting heterogeneous communication styles across administrations.

Panel C reports municipal characteristics and treatment intensity, where the median municipality has a population of 3,420 inhabitants and a surface area of 25.9 km^2, at a median altitude of 268 meters, confirming that the sample is dominated by small and medium-sized administrations typical of the Italian municipal landscape. Population is highly right-skewed (mean 10,185 *vs.* median 3,420), reflecting the presence of a small number of large cities alongside thousands of small municipalities. These three variables, log(population), altitude, and log(surface), serve as covariates in all Callaway and Sant'Anna (2021) specifications. Mean cumulative treatment intensity is approximately € 207,000, with a median of € 174,862, confirming substantial variation in

[7] Full-panel descriptive statistics covering all municipality-years (2009–2025, $N = 76{,}381$) are reported in Table A1.

program exposure even among municipalities that maintained an online presence by 2025.

Table 1: *Descriptive statistics: 2025*

Variable	N	Mean	SD	Q25	Median	Q75
Panel A: Outcomes (levels)						
Number of posts	4,493	291.80	5,218.23	65	131	245
Engagement	4,493	1,530	2,916	603	1,955	5,208
Engagement per post	4,493	23.76	141.36	7.96	15.03	27.69
Number of posts w/ link	4,493	49.49	768.40	3	11	32
Number of posts w/ image	4,493	102.35	4,714.17	3	10	29
Gulpease index	4,493	56.42	12.13	51.43	54.90	59.86
Share of posts w/ link	4,493	0.139	0.159	0.037	0.091	0.183
Share of posts w/ image	4,493	0.179	0.215	0.022	0.090	0.264
Panel B: Outcomes (transformations)						
asinh(posts)	4,493	5.386	1.267	4.868	5.568	6.194
asinh(engagement)	4,493	8.026	1.906	7.095	8.271	9.251
asinh(eng./post)	4,493	3.343	0.993	2.771	3.404	4.014
asinh(links)	4,493	2.987	1.694	1.818	3.093	4.159
asinh(images)	4,493	2.874	1.590	1.818	2.998	4.061
ln(posts)	4,493	4.720	1.208	4.190	4.883	5.505
ln(engagement)	4,493	7.345	1.868	6.404	7.579	8.558
ln(eng./post)	4,493	2.748	0.897	2.193	2.774	3.356
ln(links)	4,493	2.481	1.499	1.386	2.485	3.497
ln(images)	4,493	2.372	1.398	1.386	2.398	3.401
Panel C: Municipal characteristics and treatment						
Population	4,493	10,185	54,365	1,416	3,420	8,386
Altitude (m)	4,493	324.5	281.1	97	268	473
Surface (km^2)	4,493	44.2	57.7	13.0	25.9	52.4
Treatment intensity (€, cum.)	4,493	206,740	185,019	113,081	174,862	239,317

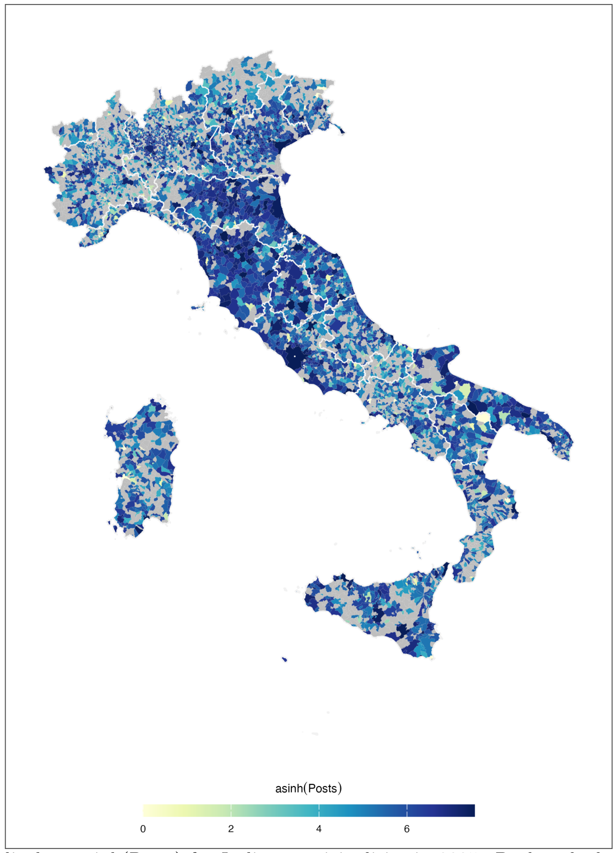
Notes: Cross-section restricted to municipalities with at least one active social-media page in 2025 ($N = 4{,}493$). Panel A reports outcome variables in levels. "N posts w/ link" and "N posts w/ image" count posts containing at least one hyperlink or image, respectively; all Instagram posts are classified as image posts. Panel B reports the same count outcomes under log and inverse-hyperbolic-sine transformations: $\ln(y) = \log(1 + y)$ and $\operatorname{asinh}(y)$. Panel C reports municipal characteristics used as covariates in the Callaway and Sant'Anna (2021) specifications ($N = 4{,}461$ due to 32 municipalities with missing covariate data from ISTAT (2025) registers) and cumulative treatment intensity in euros. Full-panel statistics (2009–2025, $N = 76{,}381$) are reported in Table A1.

Sources: Authors' elaboration based on web-scraped social-media data, *PA digitale 2026* administrative records, and ISTAT (2025) municipal boundaries.

3.4 Spatial distribution of outcomes

Figures 2–4 display the spatial distribution of the social-media outcomes across Italian municipalities in 2025. Posting intensity (Figure 2) shows broad national coverage, with notably higher activity along the Adriatic coast, in parts of Central Italy, and in the South, where many municipalities with active pages post frequently. Total engagement (Figure 3) is more spatially concentrated: high-engagement municipalities tend to cluster around larger urban centres and along the Central-Southern corridor, consistent with the idea that citizen interaction depends not only on posting behavior but also on population density and local digital-literacy levels. Finally, the Gulpease readability map (Figure 4) reveals a relatively homogeneous national pattern, with most municipalities scoring in the 40–60 range. In particular, no clear North–South gradient emerges, suggesting that linguistic complexity in institutional social-media communication is not driven primarily by geographic location.

Figure 2: *Spatial distribution of municipal posting intensity in 2025*

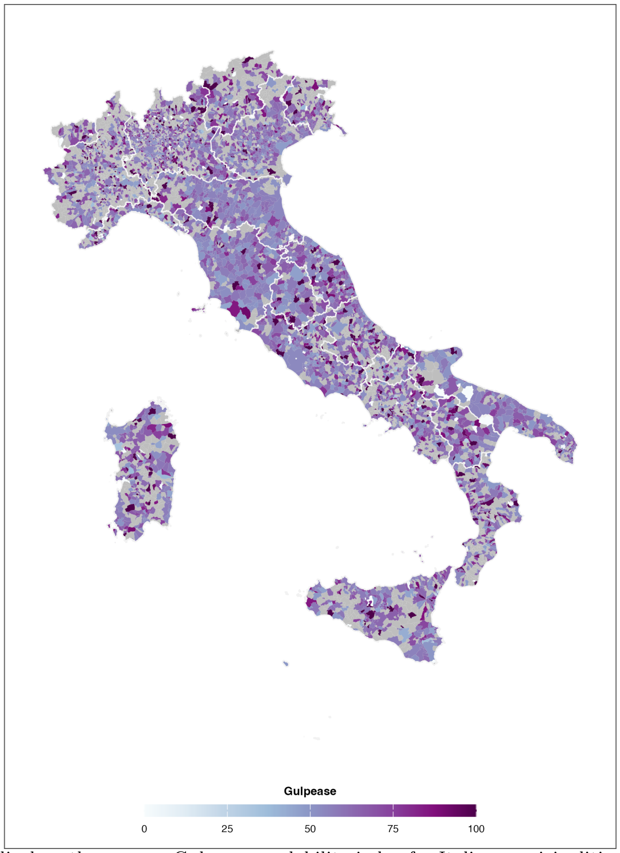


Notes: The map displays asinh(Posts) for Italian municipalities in 2025. Darker shades indicate higher posting activity on official social-media pages. Non-zero values are capped at the 99th percentile for visual clarity. Grey areas denote municipalities without a detected social-media page.
Sources: Authors' elaboration based on web-scraped social-media data and ISTAT (2025) municipal boundaries.

Figure 3: *Spatial distribution of total citizen engagement in 2025*

Notes: The map displays asinh(Engagement), where engagement is defined as the sum of likes and comments received on official municipal social-media posts in 2025. Darker shades indicate higher aggregate engagement. Non-zero values are capped at the 99th percentile for visual clarity. Grey areas denote municipalities without a detected social-media page.
Sources: Authors' elaboration based on web-scraped social-media data and ISTAT (2025) municipal boundaries.

Figure 4: *Spatial distribution of Gulpease readability in 2025*



Notes: The map displays the average Gulpease readability index for Italian municipalities in 2025. Values range from 0 to 100, with higher scores indicating more readable text. Only municipalities with at least one textual post are shown. Grey areas denote municipalities without a detected social-media page or without textual content in 2025.
Sources: Authors' elaboration based on web-scraped social-media data and ISTAT (2025) municipal boundaries.

3.5 Identification and estimation strategy

We estimate causal effects using a staggered Difference-in-Differences (DiD) design. With heterogeneous treatment timing, standard two-way fixed effects (TWFE) estimators can produce biased estimates when effects vary across cohorts, owing to "forbidden comparisons" between early and late treated units that generate negative weights (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Roth *et al.*, 2023). We therefore implement the Callaway and Sant'Anna (2021) estimator, which compares newly treated municipalities with municipalities that are not yet treated in the same period. Municipalities are grouped into cohorts by first treatment year g, and we estimate group-time average treatment effects $\text{ATT}(g, t)$, allowing treatment effects to vary across cohorts and over exposure time. Aggregation of $\text{ATT}(g, t)$ yields an overall program impact as well as cohort- and time-since-treatment profiles.

To assess dynamics and pre-trends, we complement the main estimator with an event-study specification:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{k=-K}^{K} \beta_k \cdot \mathbf{1}\{t - g_i = k\} + \varepsilon_{it} \tag{2}$$

where α_i and γ_t denote municipality and year fixed effects, respectively, and $\mathbf{1}\{t - g_i = k\}$ indicates being k periods away from first treatment g_i. We normalise $\beta_{-1} = 0$, so coefficients are interpreted relative to the last pre-treatment period. Lead coefficients test for differential pre-trends; lag coefficients trace the evolution of impacts after funding receipt (Sun and Abraham, 2021; Baker *et al.*, 2025).

4 Results

We organize results around three levels of the municipal digital divide: the first-level divide, social-media adoption (Subsection 4.1); the second-level divide, usage intensity and content composition (Subsection 4.2); and the third-level divide, communication quality and citizen resonance (Subsection 4.3). All estimates condition on three municipal-level covariates: log(population), altitude, and log(surface area), to improve precision and absorb observable heterogeneity across municipalities.

4.1 First-level divide: social-media adoption

The most striking finding is the program's effect on digital presence. Table 2 reports estimates which compares newly treated municipalities with not-yet-treated peers within the same period, netting out cohort-level confounders that can arise under standard TWFE estimation with heterogeneous treatment timing (Goodman-Bacon, 2021). The overall ATT is equal to 7 percentage points (p.p.) in the full sample (column 1), 7.6 p.p. when the comparison is restricted to funded municipalities (column 2), and 2.7 p.p. when restricted to municipalities with an observed online presence in 2025 (column 3), all statistically significant. The funded-only estimate (column 2) removes the never-treated group entirely, so that identification comes exclusively from variation in the timing of funding across municipalities that all eventually participate in the program; the fact that this estimate is slightly larger than the full-sample one suggests that selection into ever-treatment does not inflate the baseline results. Column 3 shows that even within the subsample of municipalities that have a social-media page in 2025, the program increases the probability of adoption.

Table 2: *Effect of funding on social-media adoption*

	(1) All municipalities	(2) Funded only	(3) Online presence
Callaway–Sant'Anna ATT			
Overall ATT	0.070***	0.076**	0.027**
	(0.019)	(0.031)	(0.013)
N	7,875	7,684	4,493

Notes: Outcome: social-media adoption, defined as an absorbing dummy equal to 1 from the first year the municipality publishes at least one post. Column (1) includes all Italian municipalities; column (2) restricts to funded municipalities; column (3) restricts to municipalities with an observed online presence (at least one detected social-media page). The table reports the overall ATT from Callaway and Sant'Anna (2021) with not-yet-treated municipalities as the control group. Covariates: log(population), altitude, log(surface). Clustered standard errors at the municipality level in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Sources: Authors' elaboration based on *PA digitale 2026* administrative records and web-scraped social-media data.

The cohort decomposition (Table A2) reveals that the adoption effect increases with later cohorts: the 2024 cohort shows an ATT of 6.2 p.p. ($p < 0.05$), suggesting that late adopters, municipalities that had not yet applied by 2023, experience larger first-level effects, consistent with the program reaching less digitally advanced administrations over time. Taken together, the adoption results provide robust evidence that *PA digitale 2026* helps in closing the first-level digital divide.

4.2 Second-level divide: usage intensity and content composition

Having established that the program closes the first-level divide, we now examine the second level: whether funded municipalities use social media more intensively and what type of content they produce. The analysis in this and the following subsection is restricted to the 4,493 municipalities (56.9% of all Italian municipalities) that maintained at least one active official social-media page as of 2025. Because adoption itself is a post-treatment outcome, estimates at the second and third levels capture a combination of municipalities that would not have been online without the program and those that would have been online regardless. Disentangling these two channels would require restricting the sample to municipalities that were already active before treatment, which we leave to future work. The composite effect remains policy-relevant, however, as it captures the total impact of the program on municipal digital communication, inclusive of the new adopters that the program itself generates.

Table 3 reports overall aggregated ATT estimates across all outcomes, both without and with covariates. For posting intensity, the effect on asinh(Posts) is 0.216 (with covariates), indicating a meaningful increase in posting activity relative to not-yet-treated peers; the shifted-log specification yields a consistent estimate of 0.194. Total engagement also responds positively: the effect on asinh(Engagement) is 0.267, though only marginally significant at the 10% level. The dynamic decomposition (Table A2) confirms that these effects build gradually: post-treatment coefficients at $e = 0$ and $e = 1$ are small and non-significant, whereas effects at $e = 2$ and $e = 3$ are large and statistically significant for posts ($\hat{\beta}_{e=3} = 0.437$, $p < 0.05$) and are positive, though imprecisely estimated for engagement.

Table 3: *Overall ATT estimates*

		Without covariates		With covariates	
Outcome	Transform	ATT	95% CI	ATT	95% CI
Posts	asinh(y)	0.231**	[0.044, 0.418]	0.216**	[0.013, 0.420]
Engagement	asinh(y)	0.276*	[−0.008, 0.560]	0.267*	[−0.042, 0.576]
Eng./post	asinh(y)	0.067	[−0.062, 0.197]	0.076	[−0.061, 0.213]
N posts w/ link	asinh(y)	0.152*	[−0.011, 0.316]	0.135	[−0.046, 0.317]
N posts w/ image	asinh(y)	−0.028	[−0.186, 0.130]	−0.039	[−0.215, 0.138]
Posts	ln(y)	0.209**	[0.039, 0.379]	0.194**	[0.008, 0.379]
Engagement	ln(y)	0.258*	[−0.011, 0.527]	0.246*	[−0.045, 0.538]
Eng./post	ln(y)	0.054	[−0.059, 0.166]	0.061	[−0.058, 0.179]
N posts w/ link	ln(y)	0.137*	[−0.004, 0.278]	0.123	[−0.035, 0.281]
N posts w/ image	ln(y)	−0.025	[−0.162, 0.112]	−0.036	[−0.189, 0.118]
Gulpease	level	3.645*	[−0.292, 7.583]	3.495*	[−0.373, 7.362]
Share link	level	0.008	[−0.010, 0.025]	0.010	[−0.008, 0.028]
Share image	level	−0.015	[−0.037, 0.006]	−0.010	[−0.030, 0.009]

Notes: Entries report overall aggregated ATT estimates from the Callaway and Sant'Anna (2021) estimator. "Without covariates" reports the unconditional specification; "With covariates" conditions on log(population), altitude, and log(surface). The IHS transformation $\text{asinh}(y) = \ln(y + \sqrt{y^2 + 1})$ is the preferred specification; $\ln(y)$ is reported as a robustness check. "N posts w/ link" and "N posts w/ image" count the number of posts containing at least one hyperlink or at least one image, respectively; "Share link" and "Share image" are the corresponding municipality-year proportions. All Instagram posts are classified as containing an image. Gulpease is analysed in levels (0–100 scale). Engagement = likes + comments. Control group: not-yet-treated municipalities. Confidence intervals are 95%. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Sources: Authors' elaboration.

4.3 Third-level divide: communication quality and citizen resonance

The third level of the digital divide asks whether increased digital activity translates into qualitative improvements (Scheerder *et al.*, 2017). This question has direct democratic implications: previous work has shown that the quality and accessibility of government communication online affects citizens' political knowledge, trust in institutions, and willingness to participate in local governance (Goldfinch *et al.*, 2009; Dimitrova *et al.*, 2014; Twizeyimana and Andersson, 2019). Two outcomes speak to this question: engagement per post and the Gulpease readability index.

Engagement per post (Table 3) is small and not statistically significant across both transformations (asinh: 0.076; ln: 0.061), suggesting that the rise in aggregate engagement documented in Section 4.2 is driven primarily by increased posting volume rather than by higher per-post resonance: municipalities post more, and this generates more interactions in aggregate, but each individual post does not attract meaningfully more citizen attention than before.[8] The Gulpease readability index presents a more nuanced picture. The overall ATT is positive (+3.50 points) and marginally significant (Table 3). The event-study dynamics reinforce this reading: effects are small and imprecise in the immediate post-treatment periods ($k = 0$ and $k = 1$) but point estimates trend upward over time. The cohort decomposition (Table A2) is particularly informative: the $e = 3$ dynamic estimate is large and highly significant (+6.62 points, $p < 0.01$), indicating that municipalities that have been treated for three years show a substantial improvement in readability. This trajectory is suggestive of a gradual closing of the quality dimension of the third-level divide, consistent with institutional learning, though the post-treatment window extends only to $k = 3$, and longer time series will be needed to confirm whether convergence is sustained.

5 Conclusion

This paper studies the impact of digitalization subsidies on citizen-facing public services, combining high-frequency digital trace data with administrative records on public investment. Using Italian municipalities as a case study, we exploit the staggered rollout of the *PA digitale 2026* program to identify causal effects across three dimensions of the municipal digital divide: access, usage, and outcomes. Empirically, we implement a multi-period Difference-in-Differences design with heterogeneous treatment timing, complemented by event-study analysis, and measure outcomes using social-media activity as a scalable proxy for public communication.

Our results reveal a clear gradient of effectiveness across the three levels of

[8]The event-study dynamics (Figure A4) confirms this reading: post-treatment coefficients remain small and statistically non-significant, with wide confidence intervals consistent with the null ATT.

the digital divide. At the first level, digitalization subsidies have strong and robust effects: municipalities receiving funding are significantly more likely to adopt social media, indicating that the program effectively expands access to digital communication channels. At the second level, treated municipalities increase posting activity and generate higher total engagement, with effects that build over time. The additional content is predominantly text-based and increasingly link-rich, suggesting a shift toward more informational forms of institutional communication. At the third level, however, the effects are more limited: engagement per post does not increase, and improvements in communication quality, measured by readability, emerge only gradually. This pattern indicates that, while digital investment expands digital activity, its translation into more effective communication requires time and accumulated institutional experience.

These findings have several policy implications. First, they show that infrastructure-oriented digitalization policies can successfully close the access dimension of the digital divide in public administration. In other words, in the absence of the program, many municipalities would likely remain outside digital communication channels. Second, they highlight a persistent gap between access and effective use: increases in total engagement are driven by higher content volume rather than improved citizen resonance, suggesting that supply-side expansion alone is insufficient to enhance communication effectiveness. Third, the gradual improvement in readability points to a learning process, implying that the third-level digital divide is not structural but can be reduced over time. However, this also suggests that complementary investments in digital skills, communication capacity, and organizational practices may be necessary to fully realise the benefits of digitalization.

More broadly, the results shed light on the mechanisms through which digitalization subsidies operate. Because *PA digitale 2026* funds infrastructure rather than communication directly, the observed effects on social media reflect spillovers from a broader institutional digital transformation. As municipalities upgrade digital systems, they produce more content and increasingly rely on informational link-based communication. This shift, however, does not immediately translate into higher quality or more engaging content, reinforcing the distinction between digital activity and digital effectiveness.

The paper contributes to three strands in the literature. First, it provides causal evidence on the digital divide in public institutions, extending a framework traditionally applied to individuals to the organizational level of local governments. Second, it demonstrates the value of digital trace data as high-frequency outcome measures for policy evaluation, enabling near real-time assessment of policy impacts. Third, it contributes to the literature on e-government and democratic governance by showing that infrastructure investments generate measurable improvements in transparency and communication, but that the quality dimension — crucial for participation and accountability — adjusts more slowly.

Several limitations qualify these findings. Our outcomes capture online communication rather than broader measures of citizen trust, satisfaction, or service uptake. The program only affects social media uptake indirectly; thus our estimates reflect spillovers from infrastructure investment rather than direct interventions in communication. The post-treatment window is relatively short, limiting our ability to assess long-run convergence in communication quality. Finally, second- and third-level effects combine new adopters with already active municipalities, yielding a composite estimate of the program's overall impact.

These limitations point to directions for future research. Linking digital communication outcomes to measures of citizen trust and participation would clarify whether improvements in online activity translate into broader democratic gains. Extending the analysis over a longer time horizon would allow for a more definitive assessment of convergence in communication quality. Incorporating spatial interactions could shed light on potential spillovers across municipalities. More generally, understanding how digital investments translate into public value remains an open and policy-relevant question.

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Appendix

A.1 Readability and the Gulpease index

To capture the quality and accessibility of institutional language, we measure textual clarity using the Gulpease index, a readability metric specifically tailored to the Italian language (Lucisano *et al.*, 1988). The index summarises text complexity on a 0–100 scale, where higher values indicate easier-to-read content. Formally, for a given text, the Gulpease index is computed as:

$$\text{Gulpease} = 89 + \frac{300 \times \text{sentences} - 10 \times \text{letters}}{N} \tag{3}$$

where N denotes the total number of words, and the numerator combines syntactic complexity (sentences per text) and lexical complexity (letters per text). An equivalent representation expresses the index in terms of average characters per word (CP) and words per sentence (PF):

$$G = 89 - 10\,\text{CP} + \frac{300}{\text{PF}} \tag{4}$$

Standard thresholds map the score to educational attainments: values below 80 indicate difficulty for readers with elementary education, below 60 for middle school, and below 40 for high school graduates. Beyond its original application, the Gulpease index has been used in several institutional and policy-relevant contexts including university reporting, central-bank communication, regulatory documentation, and political discourse, supporting its suitability for digital public-content analysis (Allini *et al.*, 2017; Ferrara and Angino, 2022; Blinder *et al.*, 2024; Alfano and Guarino, 2024; Durante *et al.*, 2019). Recent work has also studied the readability of Italian administrative texts from the reader's perspective, finding that bureaucratic language poses significant comprehension barriers even for educated citizens (Miliani *et al.*, 2022).

In our setting, Gulpease is computed on the textual content of municipalities' social-media posts and aggregated at the municipality-year level. Because readability is undefined when no textual content is produced, municipality-years with zero posts are excluded from the readability outcome to avoid mechanically assigning a “readability” score to missing communication.

A.2 Additional maps

Figure A1 shows the spatial distribution of log-transformed *PA digitale 2026* funding intensity across Italian municipalities. The transformation compresses the highly skewed distribution and reveals that funding is geographically diffuse, with higher per-municipality amounts in Centre-South Italy and the islands, mirroring the NRRP’s cohesion objectives.

Figure A1: *PA digitale 2026 funding intensity,* ln(*euros*)*, by municipality*

Notes: The map displays log-transformed funding intensity, computed as ln(total funding) for each municipality. The transformation compresses the highly skewed distribution and reveals broader geographic variation. Grey areas denote municipalities not in the sample.
Sources: Authors’ elaboration based on *PA digitale 2026* administrative records and ISTAT municipal boundaries (ISTAT, 2025).

A.3 Full-panel descriptive statistics

Table A1 reports summary statistics for the full municipality-year panel (2009–2025, $N = 76{,}381$). In contrast to the 2025 cross-section presented in the main text, the full panel includes all municipality-years, many of which record zero posts and zero engagement. This large mass of zeros reflects the fact that many municipalities had not yet established an official social-media page, or maintained an inactive page, in earlier years of the observation window. Rather than representing mere missing data, this pattern is informative: it captures the substantial heterogeneity in digital capacity across Italian local administrations, and likely reflects persistent digital divides related to municipal size, administrative resources, geographic remoteness, and the availability of technical staff. The prevalence of zeros declines sharply over time as municipalities gradually adopt social-media communication, a trend that the programme itself may accelerate.

Table A1: *Descriptive statistics: full panel (2009–2025)*

Variable	N	Mean	SD	P25	Median	P75
Panel A: Outcomes (levels)						
Number of posts	76,381	61.10	2,138.63	0	0	0
Engagement per post	76,381	2.69	35.51	0	0	0
N posts w/ link	76,381	14.18	334.73	0	0	0
N posts w/ image	76,381	24.39	2,043.08	0	0	0
Gulpease (outcome)	76,381	7.35	19.58	0	0	0
Share link	76,381	0.020	0.083	0	0	0
Share image	76,381	0.023	0.101	0	0	0
Panel B: Outcomes (transformations)						
ln(Posts)	76,381	0.59	1.62	0	0	0
ln(Engagement)	76,381	0.91	2.47	0	0	0
ln(Eng./post)	76,381	0.34	0.95	0	0	0
ln(Links)	76,381	0.31	1.04	0	0	0
ln(Images)	76,381	0.29	0.93	0	0	0
Panel C: Municipal characteristics and treatment						
Population	76,381	10,275	54,346	1,497	3,534	8,493
Altitude (m)	76,381	324.3	280.7	97.0	268.0	473.0
Surface (km^2)	76,381	44.2	57.7	13.0	25.9	52.2

Notes: Municipality-year panel, 2009–2025 ($N = 76{,}381$). The large prevalence of zeros at P25, Median, and P75 in Panels A and B reflects the many municipality-years in which a social-media page had not yet been created or was inactive, capturing heterogeneous digital capacity across municipalities. "N posts w/ link" and "N posts w/ image" count posts containing at least one hyperlink or image; all Instagram posts are classified as image posts. The Gulpease outcome variable is defined as the average Gulpease index for municipality-years with at least one textual post and zero otherwise. Log-transformed outcomes use $\ln(y) = \log(1 + y)$. Panel C reports municipal characteristics from ISTAT registers used as covariates in the Callaway and Sant'Anna (2021) specifications, and cumulative treatment intensity in euros.

Sources: Authors' elaboration based on web-scraped social-media data, *PA digitale 2026* administrative records, and ISTAT municipal registers.

A.4 ATT decomposition by cohort and exposure time

Table A2 decomposes the overall ATT estimates reported in Table 3 along two dimensions: by treatment cohort (year of first funding) and by exposure time ($e = 0, 1, 2, 3$ years since treatment). The cohort decomposition reveals whether effects are concentrated among early or late adopters of the programme, while the dynamic decomposition traces how effects evolve with accumulated post-treatment experience. For count outcomes, both the $\ln(y)$ and $\text{asinh}(y)$ specifications are reported; for Gulpease, share link, share image, and adoption, only the level specification applies. The vast majority of treated municipalities belong to the 2022 cohort (3,709 out of 4,410 ever-treated), followed by the 2023 cohort (660), with only 31 and 10 municipalities first treated in 2024 and 2025 respectively; estimates for later cohorts are therefore less precise.

Several patterns stand out. First, for posting intensity, the $e = 0$ coefficient is essentially zero, the $e = 1$ coefficient is small and insignificant, and effects become statistically significant at $e = 2$ (0.340, $p < 0.05$) and $e = 3$ (0.437, $p < 0.05$), confirming that the posting effect requires roughly two years to materialise fully. Second, the Gulpease dynamic profile is particularly informative: the $e = 3$ estimate is large and highly significant (+6.62 points, $p < 0.01$), supporting the catch-up interpretation discussed in Section 4.3. Third, the adoption effect increases across later cohorts (2.6 p.p. for 2022, 3.3 p.p. for 2023, 6.2 p.p. for 2024, all $p < 0.05$), consistent with the programme reaching less digitally advanced municipalities over time.

Table A2: *ATT decomposition by cohort and exposure time*

Outcome	Type	ATT	SE	95% CI
Posts	Overall	0.194**	(0.095)	[0.008, 0.379]
	Cohort 2022	0.197**	(0.092)	[0.016, 0.378]
	Cohort 2023	0.164	(0.117)	[−0.065, 0.394]
	Cohort 2024	0.219	(0.246)	[−0.264, 0.702]
	Cohort 2025	0.057	(0.508)	[−0.939, 1.053]
	$e = 0$	−0.004	(0.005)	[−0.013, 0.005]
	$e = 1$	0.041	(0.027)	[−0.012, 0.094]
	$e = 2$	0.340**	(0.168)	[0.010, 0.670]
	$e = 3$	0.437**	(0.215)	[0.015, 0.858]
Engagement	Overall	0.246*	(0.149)	[−0.045, 0.538]
	Cohort 2022	0.250*	(0.145)	[−0.034, 0.533]
	Cohort 2023	0.216	(0.189)	[−0.155, 0.587]
	Cohort 2024	0.383	(0.426)	[−0.452, 1.218]
	Cohort 2025	0.707	(0.980)	[−1.215, 2.628]
	$e = 0$	−0.003	(0.007)	[−0.017, 0.011]
	$e = 1$	0.055	(0.045)	[−0.034, 0.144]
	$e = 2$	0.453	(0.278)	[−0.092, 0.999]
	$e = 3$	0.527	(0.321)	[−0.102, 1.156]
Eng./post	Overall	0.061	(0.061)	[−0.058, 0.179]
	Cohort 2022	0.059	(0.058)	[−0.055, 0.174]
	Cohort 2023	0.063	(0.080)	[−0.095, 0.221]
	Cohort 2024	0.229	(0.198)	[−0.160, 0.618]
	Cohort 2025	0.704	(0.578)	[−0.429, 1.837]
	$e = 0$	0.001	(0.003)	[−0.006, 0.007]

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Table A2 continued from previous page

Outcome	Type	ATT	SE	95% CI
	$e = 1$	0.017	(0.020)	[−0.022, 0.057]
	$e = 2$	0.126	(0.120)	[−0.110, 0.362]
	$e = 3$	0.107	(0.122)	[−0.133, 0.347]
Gulpease	Overall	3.495*	(1.973)	[−0.373, 7.362]
	Cohort 2022	3.312*	(1.900)	[−0.411, 7.035]
	Cohort 2023	4.681*	(2.669)	[−0.551, 9.912]
	Cohort 2024	10.848*	(5.541)	[−0.012, 21.709]
	Cohort 2025	−6.331	(15.401)	[−36.516, 23.855]
	$e = 0$	0.141	(0.128)	[−0.110, 0.392]
	$e = 1$	1.103	(1.004)	[−0.865, 3.071]
	$e = 2$	6.635	(5.540)	[−4.224, 17.494]
	$e = 3$	6.620***	(2.388)	[1.939, 11.300]
Share link	Overall	0.010	(0.009)	[−0.008, 0.028]
	Cohort 2022	0.010	(0.009)	[−0.007, 0.027]
	Cohort 2023	0.008	(0.013)	[−0.017, 0.033]
	Cohort 2024	−0.032	(0.020)	[−0.072, 0.007]
	Cohort 2025	0.034	(0.031)	[−0.027, 0.095]
	$e = 0$	−0.001	(0.001)	[−0.002, 0.000]
	$e = 1$	0.003	(0.004)	[−0.004, 0.010]
	$e = 2$	0.016	(0.019)	[−0.021, 0.053]
	$e = 3$	0.023	(0.017)	[−0.011, 0.057]
Adoption	Overall	0.027**	(0.013)	[0.001, 0.052]
	Cohort 2022	0.026**	(0.013)	[0.001, 0.050]
	Cohort 2023	0.033**	(0.017)	[0.001, 0.066]
	Cohort 2024	0.062**	(0.025)	[0.014, 0.111]
	Cohort 2025	0.148	(0.128)	[−0.104, 0.400]
	$e = 0$	0.001**	(0.001)	[0.000, 0.002]
	$e = 1$	0.011**	(0.005)	[0.001, 0.021]
	$e = 2$	0.057*	(0.030)	[−0.001, 0.115]
	$e = 3$	0.040*	(0.023)	[−0.005, 0.085]
N links	Overall	0.123	(0.081)	[−0.035, 0.281]
	Cohort 2022	0.133*	(0.079)	[−0.022, 0.289]
	Cohort 2023	0.056	(0.099)	[−0.137, 0.250]
	Cohort 2024	−0.209	(0.223)	[−0.645, 0.228]
	Cohort 2025	0.231	(0.255)	[−0.268, 0.730]
	$e = 0$	−0.006	(0.006)	[−0.017, 0.005]
	$e = 1$	0.023	(0.024)	[−0.024, 0.069]
	$e = 2$	0.206	(0.138)	[−0.064, 0.475]
	$e = 3$	0.298	(0.190)	[−0.075, 0.671]
Share image	Overall	−0.010	(0.010)	[−0.030, 0.009]
	Cohort 2022	−0.010	(0.010)	[−0.028, 0.009]
	Cohort 2023	−0.015	(0.014)	[−0.042, 0.011]
	Cohort 2024	−0.006	(0.047)	[−0.098, 0.086]
	Cohort 2025	−0.108	(0.074)	[−0.253, 0.037]
	$e = 0$	0.001	(0.001)	[−0.001, 0.003]

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Table A2 continued from previous page

Outcome	Type	ATT	SE	95% CI
	$e = 1$	−0.002	(0.004)	[−0.010, 0.006]
	$e = 2$	−0.016	(0.022)	[−0.058, 0.026]
	$e = 3$	−0.027	(0.021)	[−0.069, 0.015]
N images	Overall	−0.036	(0.078)	[−0.189, 0.118]
	Cohort 2022	−0.023	(0.079)	[−0.177, 0.131]
	Cohort 2023	−0.122	(0.088)	[−0.294, 0.050]
	Cohort 2024	−0.146	(0.231)	[−0.598, 0.306]
	Cohort 2025	−0.626	(0.383)	[−1.376, 0.124]
	$e = 0$	0.007	(0.008)	[−0.009, 0.022]
	$e = 1$	−0.023	(0.046)	[−0.113, 0.067]
	$e = 2$	−0.032	(0.130)	[−0.287, 0.223]
	$e = 3$	−0.105	(0.179)	[−0.457, 0.247]

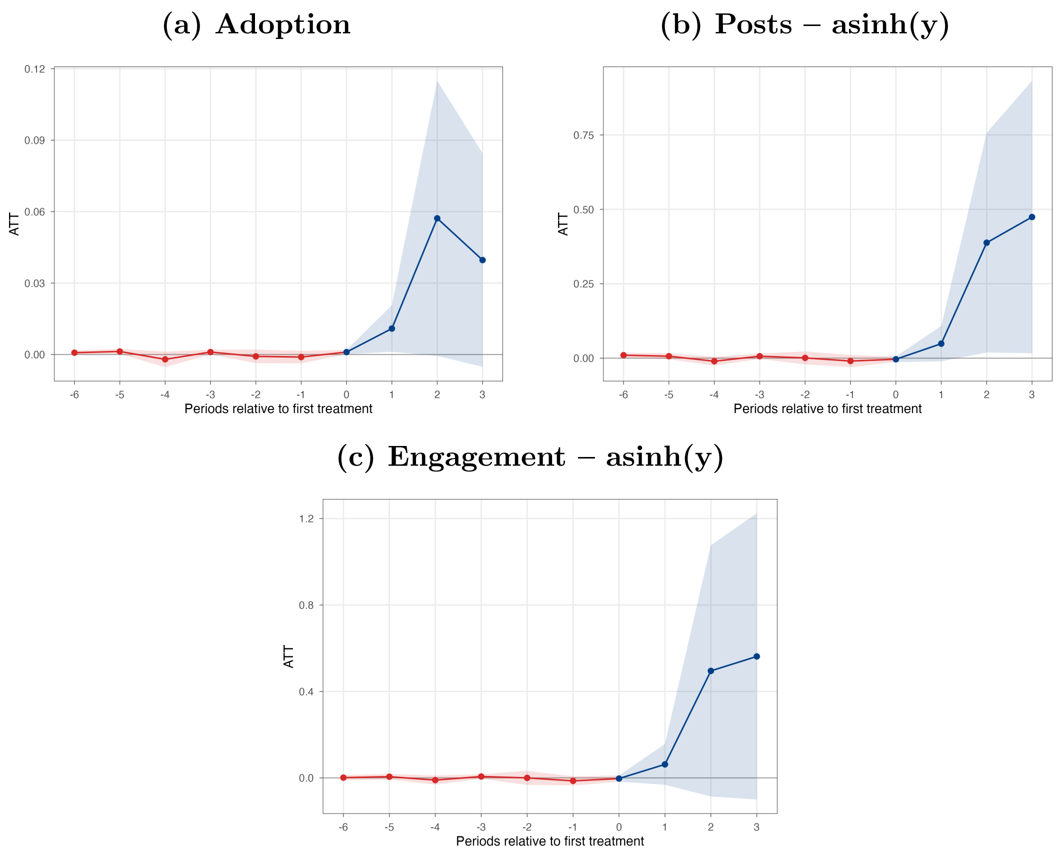
Notes: Decomposition of the overall ATT from the Callaway and Sant'Anna (2021) estimator with covariates (log(population), altitude, log(surface)). Control group: not-yet-treated municipalities. "Cohort" rows report ATT by year of first treatment; "e" rows report ATT by exposure time (years since first funding receipt). Count outcomes report the $\ln(y)$ specification. Cohort sizes: 2022 (n = 3,709), 2023 (n = 660), 2024 (n = 31), 2025 (n = 10). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
Sources: Authors' elaboration.

A.5 Event-study estimates

Figure A2 presents event-study estimates for adoption and communication intensity.[9] Pre-treatment coefficients are small and statistically indistinguishable from zero across all outcomes, supporting the plausibility of parallel trends (Baker *et al.*, 2025). Post-treatment effects on posting intensity (panel b) and total engagement (panel c) grow progressively: estimated effects at event time 0 are modest and imprecise, whereas coefficients become larger and more precisely estimated from $k = 1$ onward. For engagement, the acceleration is even more pronounced, with sizeable estimates emerging at $k = 1$, consistent with an expanding online audience that takes time to build.

[9]The corresponding estimates under the $\ln(y)$ transformation are reported in Figure A5 and yield substantively identical dynamics.

Figure A2: *Event-study estimates: adoption and communication intensity*

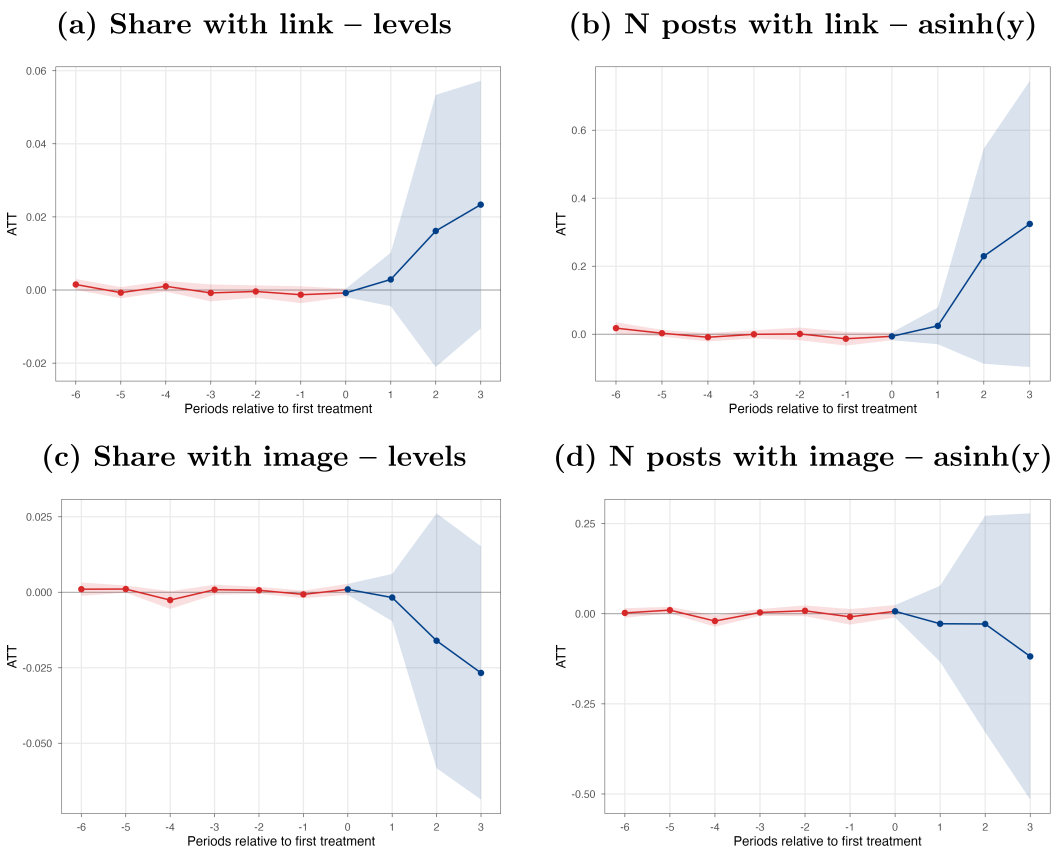


Notes: Each panel plots event-study coefficients $\hat{\beta}_k$ from the Callaway and Sant'Anna (2021) staggered DiD design with covariates (log(population), altitude, log(surface)), where k denotes years relative to first funding receipt ($k = 0$). The reference period is $k = -1$. Red markers indicate pre-treatment periods; blue markers indicate post-treatment periods. Shaded areas are 95% pointwise confidence intervals. Panel (a): adoption (binary indicator). Panels (b)–(c): asinh(y) transformation. Engagement = likes + comments.
Sources: Authors' elaboration.

Figure A3 turns to content composition. The number of posts containing hyperlinks (panel b) follows an upward trajectory from $k = 1$ onward that parallels the overall posting pattern (Figure A2, panel b), suggesting that a substantial share of the additional content is rich in outbound references, links to institutional websites, service portals, or news updates, consistent with an informational communication style. The share of posts containing links (panel a) also shows a modest upward trend, though the effect is small in magnitude and not statistically significant in most post-treatment periods.

By contrast, the share of posts containing images (panel c) displays a negative post-treatment trend: point estimates turn downward from $k = 1$ and become more negative by $k = 3$, although confidence intervals remain wide. This pattern points to a change in the content mix: newly active municipalities rely more heavily on text-based communication rather than on visual media. The declining image share follows naturally from the large expansion of posting volume: the new posts are predominantly textual, diluting the proportion of image-based content in the municipality's communication portfolio. Panel (d) confirms that the absolute number of image posts does not increase significantly, reinforcing the interpretation that the programme stimulates text-oriented institutional content rather than visual engagement.

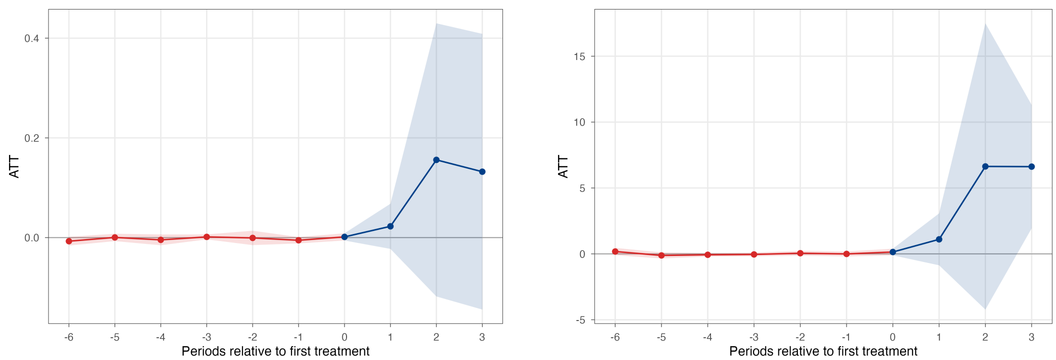
Figure A3: *Event-study estimates: content composition*



Notes: Each panel plots event-study coefficients $\hat{\beta}_k$ from the Callaway and Sant'Anna (2021) staggered DiD design with covariates (log(population), altitude, log(surface)), where k denotes years relative to first funding receipt ($k = 0$). The reference period is $k = -1$. Red markers indicate pre-treatment periods; blue markers indicate post-treatment periods. Shaded areas are 95% pointwise confidence intervals. Panels (a) and (c): municipality-year proportions (levels). Panels (b) and (d): asinh(y) transformation. All Instagram posts are classified as image posts.
Sources: Authors' elaboration.

Figure A4: *Event-study estimates: communication quality and citizen resonance*

(a) Eng. per post – asinh(y) **(b) Gulpease – levels**



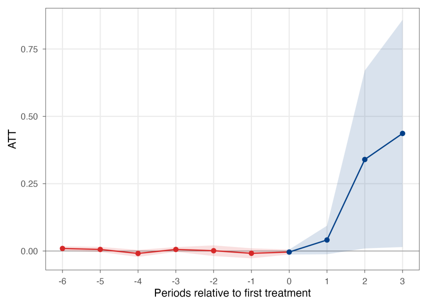
Notes: Each panel plots event-study coefficients $\hat{\beta}_k$ from the Callaway and Sant'Anna (2021) staggered DiD design with covariates (log(population), altitude, log(surface)), where k denotes years relative to first funding receipt ($k = 0$). The reference period is $k = -1$. Red markers indicate pre-treatment periods; blue markers indicate post-treatment periods. Shaded areas are 95% pointwise confidence intervals. Panel (a): asinh(y) transformation; engagement = likes + comments. Panel (b): Gulpease readability index (levels, 0–100 scale).
Sources: Authors' elaboration.

A.6 Event-study estimates under log transformation

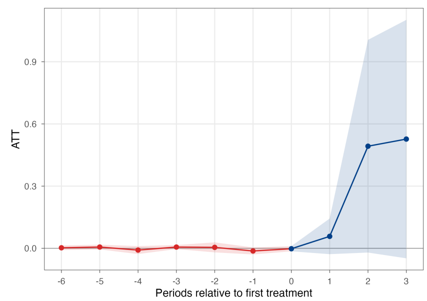
Figure A5 replicates the analysis (Figure A2, panels b–d and g) using the log transformation ln(y) in place of asinh(y). The dynamics are substantively identical for all count outcomes: pre-treatment coefficients are close to zero, and post-treatment effects exhibit the same gradual ramp-up pattern for posts, engagement, and the number of link posts, with engagement per post remaining small and insignificant. The close agreement between the two transformations is expected given that our outcomes are measured in natural count units, so that the unit-dependence concern raised by Chen and Roth (2024) has limited bite in this setting.

Figure A5: *Event-study estimates under* ln(y) *transformation (robustness)*

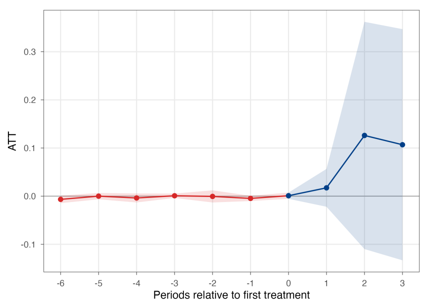
(a) Posts – ln(y)



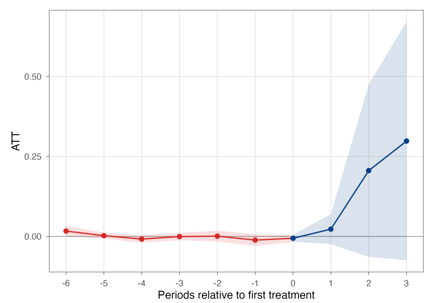
(b) Engagement – ln(y)



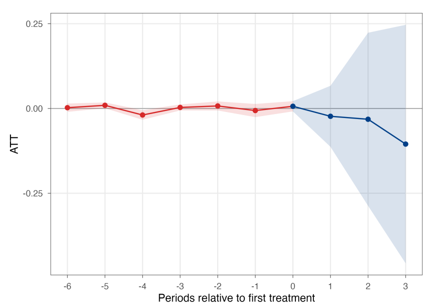
(c) Eng. per post – ln(y)



(d) N posts with link – ln(y)



(e) N posts with image – ln(y)



Notes: Robustness check using ln(y) in place of asinh(y). Each panel plots event-study coefficients $\hat{\beta}_k$ from the Callaway and Sant'Anna (2021) staggered DiD design, where k denotes years relative to first funding receipt ($k = 0$). The reference period is $k = -1$. Red markers indicate pre-treatment periods; blue markers indicate post-treatment periods. Shaded areas are 95% pointwise confidence intervals. Panels (a)–(c) correspond to Figure A2, panels (b)–(d). Panel (d): number of posts with at least one link (ln(y)). Panel (e): number of posts with at least one image (ln(y)). Compare with Figures A2 and A4 (main specification).
Sources: Authors' elaboration.