

Timing, Networks and Short-Video Engagement

Evidence from 1.4 Billion TikTok Posts and Hourly National Internet Latency

KASPR Research

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Abstract

When a post goes live matters for how far it travels. We quantify two parts of that timing: the hour and day at which posts typically perform best, and the state of the national internet in the posting hour. We match 1.42 billion TikTok posts published in 2025 in 234 countries to KASPR’s hourly national measurements of latency and jitter, and estimate one model with country and week fixed effects, local hour-of-day and day-of-week effects, and controls for post type, paid distribution and the age of the engagement snapshot. Each additional 10 milliseconds of latency in the posting hour is associated with 1.3% fewer views, 0.8% fewer likes and 1.1% fewer comments; jitter has no consistent effect, and engagement per view does not change. Timing within the day matters more: posts published at 03:00 local time get 21% fewer views than posts published at 16:00, and moving a 19:00 post one hour earlier is typically worth about 3% more views, likes and comments. Weekends are 2.5% below Monday for views. The estimates are aggregate (across countries and months) and descriptive of typical outcomes; we turn them into a simple rule for evaluating past posting times, which powers KASPR’s post-timing check.

1 Introduction

Creators and campaign managers choose posting times on rules of thumb. Platforms distribute content through recommenders that respond to early engagement, so the first hours after posting carry weight: a post that reaches its audience when it is awake and when the network delivers it smoothly has a better start. Two literatures speak to this. Quality-of-experience research shows that start-up delay and stalls reduce viewing (Dobrian et al., 2011; Krishnan and Sitaraman, 2013; Nam et al., 2016), and experiments at large web services show that added latency reduces use and revenue (Brutlag, 2009; Kohavi et al., 2009). Research on social media shows strong daily and weekly cycles in activity (Golder and Macy, 2011) and competition for attention among posts published at the same time (Weng et al., 2012).

We bring both together at a scale that has not been possible before. On the content side, the datasocial release of TikTok metadata (datasocial, 2026) gives posting time, country and engagement counts for every post. On the network side, KASPR measures the responsiveness of internet connections in every country every hour (KASPR, 2026). Joining the two by country and posting hour gives every post the network conditions of its first hour, and its local time and day.

This paper reports one model and its main results, chosen to be directly usable: every coefficient is an aggregate effect across countries and months, expressed in percent, and the whole parameter set is published for KASPR’s post-timing check. Robustness checks and heterogeneity analyses are documented in the technical appendix (analysis/RESULTS.md).

2 Data

TikTok posts. The release contains metadata for 5.6 billion TikTok videos (datasocial, 2026). We use the 1.47 billion posts published in 2025: posting time (UTC), country, type (video or photo post), duration, paid-distribution flag, and views, likes, comments, shares, saves and downloads

Some networks barely move; others swing by tens of milliseconds

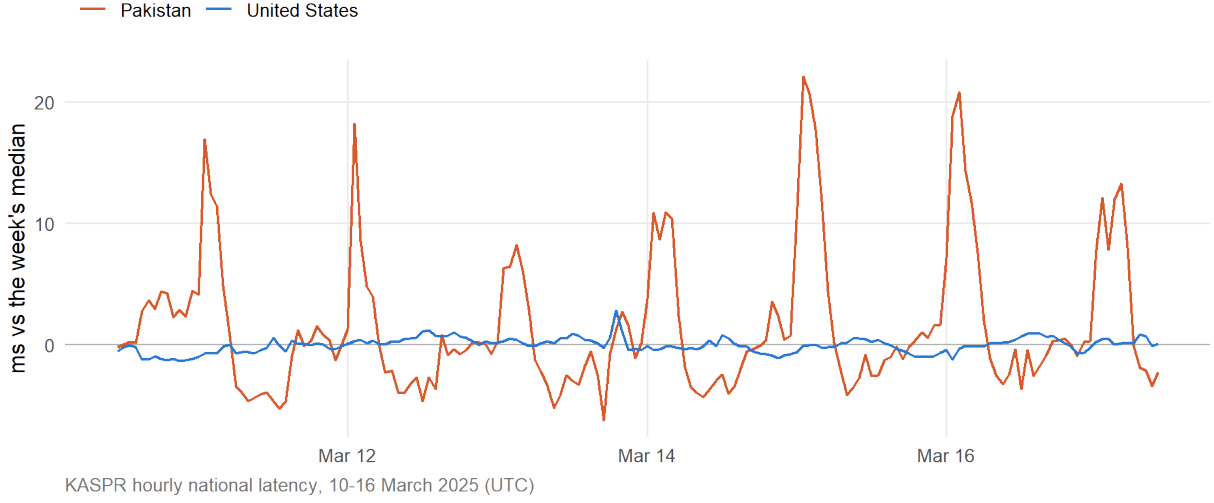


Figure 1: Hourly national latency in one week of March 2025, relative to the week’s median: the United States and Pakistan.

at a snapshot taken weeks to months after posting. 85% of posts carry the country code of the United States.

KASPR network measurements. For each country and UTC hour, KASPR reports the mean round-trip latency of responding addresses and its standard deviation (jitter), both in milliseconds, with support counts and reliability flags (KASPR, 2026). National latency is stable in mature markets and volatile in others (Figure 1): in a typical week the US series moves within about ± 2 ms of its median, Pakistan’s by 20 ms.

The join. Each post is matched to its country and UTC posting hour (99.95% match) and given its local hour and day of week. We keep reliable hours (at least 30 responding addresses, regular measurement days): 1.42 billion posts in 234 countries over 53 weeks.

3 Method

For post i in country c , published in UTC hour t (local hour h , local day of week w , calendar week k), we estimate

$$\log(1 + y_{ict}) = \beta_L \frac{L_{ct}}{10} + \beta_J \frac{J_{ct}}{10} + \eta_h + \omega_w + x'_i \gamma + \alpha_c + \kappa_k + \varepsilon_{ict}, \quad (1)$$

where L and J are latency and jitter in ms, so β_L is the effect of 10 additional milliseconds; η_h are local hour-of-day effects (reference 16:00); ω_w local day-of-week effects (reference Monday); x_i controls for post type, paid distribution and the log age of the engagement snapshot; and α_c and κ_k are country and week fixed effects. All effects are additive and pooled across countries and months. Coefficients on the log outcome are read as percentage changes ($100(e^\beta - 1)$). Standard errors are clustered by country-day.

Because the network measures, the local hour and the day of week are constant within a country-hour, the regression on 1.42 billion posts equals a post-count-weighted regression on 6.5 million cells (country $\times$ hour $\times$ post type $\times$ ad flag $\times$ duration bin), which we estimate with `fixest` (Bergé, 2018) after a single aggregation pass in DuckDB (Raasveldt and Mühleisen, 2019).

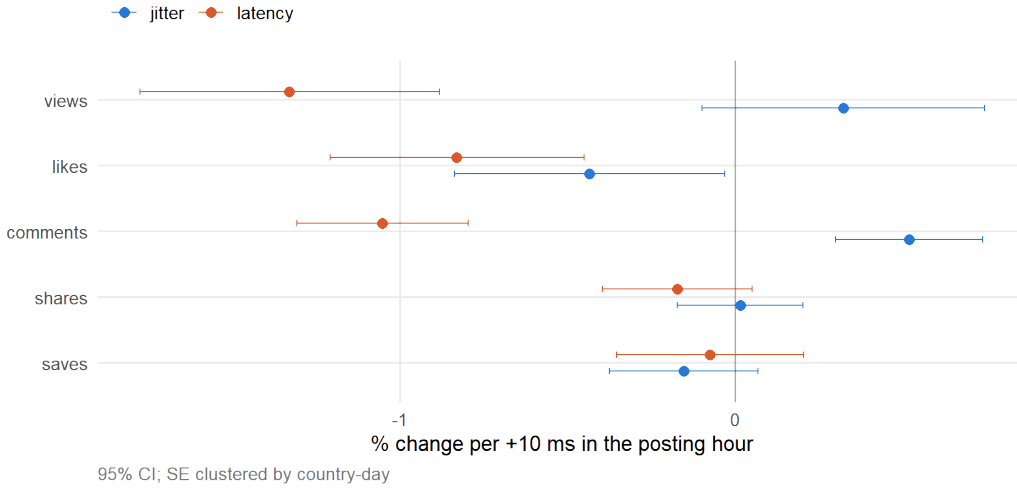
Table 1: Main model: effect of +10 ms of latency and of jitter in the posting hour (% change; 90% interval).

outcome	latency, +10 ms		jitter, +10 ms	
	%	90% interval	%	90% interval
views	-1.33***	[-1.70, -0.95]	+0.32	[-0.03, +0.68]
likes	-0.83***	[-1.15, -0.51]	-0.43*	[-0.77, -0.10]
comments	-1.05***	[-1.27, -0.84]	+0.52***	[+0.33, +0.70]
shares	-0.17	[-0.36, +0.02]	+0.02	[-0.14, +0.17]
saves	-0.08	[-0.31, +0.16]	-0.15	[-0.34, +0.03]
downloads	-0.01	[-0.02, +0.01]	+0.01	[+0.00, +0.03]
engagement rate (points)	+0.0001		+0.0002	

1,417,013,361 posts in 6,489,089 cells, 234 countries, 53 weeks. Model (1): country and week fixed effects; local hour-of-day and day-of-week effects; controls for post type, paid distribution and log snapshot age. SE clustered by country-day. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. R^2 0.44 (views), 0.39 (likes), 0.51 (comments).

Slower networks, less engagement

Latency lowers views, likes and comments; shares and saves barely move; jitter has no consistent effect

**Figure 2:** Effect of +10 ms of latency and jitter in the posting hour, 95% intervals.

4 Results

4.1 The network in the posting hour

Table 1 and Figure 2 report the network coefficients. An additional 10 ms of national latency in the posting hour is associated with 1.33% fewer views, 0.83% fewer likes and 1.05% fewer comments, all highly significant. Shares, saves and downloads do not move measurably, and neither does the engagement rate (engagement per view): slower hours reduce how far a post travels, not how intensively its viewers engage. Jitter, conditional on latency, has no consistent effect: small and of mixed sign across outcomes.

Figure 3 shows the shape of the latency relationship, plotting engagement against how far the posting hour's latency deviated from what country, week, weekday and hour predict. Within a few milliseconds of the expected level the relationship is steep: hours 3–6 ms slower than expected have 2.1% fewer views and 1.5% fewer likes, hours 3–6 ms faster about 2% more. Beyond roughly 10 ms, views and likes stop falling while comments keep falling (about -2.5%). Large latency spikes coincide with other changes in who is online and posting, so the linear coefficient should be applied to ordinary hour-to-hour differences, not to outages; KASPR's tools cap the network component at $\pm 3\%$.

A few extra milliseconds cost views, likes and comments

Beyond ~10 ms views and likes stop falling, comments keep falling: do not extrapolate to outages

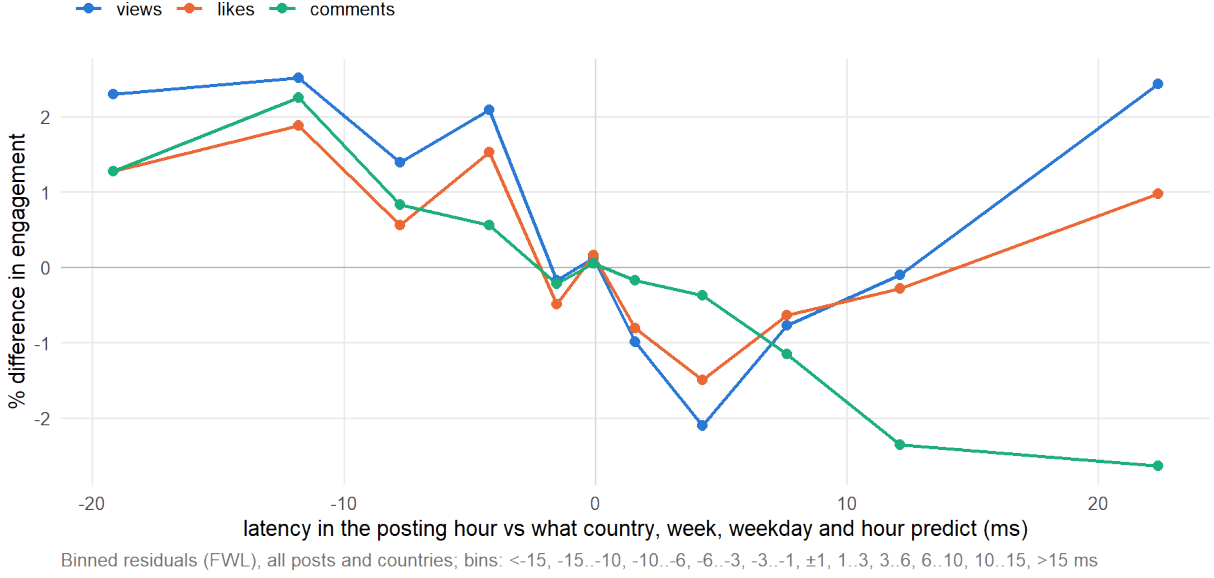


Figure 3: Engagement against latency deviations in the posting hour (binned residuals from model (1) without the latency term).

4.2 The hour and the day

The local hour of posting is the larger lever (Figure 4). Holding country, week, day of week and network conditions fixed, posts published at 16:00 local time do best. Posts published at 03:00 get 21% fewer views, 30% fewer likes and 19% fewer comments; the curve rises steeply through the morning, is flat from about 12:00 to 17:00 and falls through the evening, reaching -10% by 23:00. Likes are the most sensitive to the hour, comments the least.

Day of week matters much less (Figure 5). Monday posts do best on views; Saturday and Sunday posts get about 2.5% fewer views, and the weekday differences are within one percent. For comments only Saturday stands out (-1.1%).

4.3 From estimates to a timing rule

Because the model is additive, the typical effect of moving a post from hour a to hour s is the difference of their hour effects, plus the difference of the day effects if the move crosses midnight, plus, where the market's network series is known, the latency term:

$$\Delta\% = 100 \left[\exp(\eta_s - \eta_a + \omega_{w(s)} - \omega_{w(a)} + \beta_L(L_s - L_a)/10) - 1 \right]. \quad (2)$$

Figure 6 tabulates the hour part for views for every posting hour and moves of one or two hours. Two regions stand out: early-morning posts (06:00–09:00) gain 3–10% from a one-to-two-hour delay, and evening posts (19:00–21:00) gain 2–5% from posting one to two hours earlier. Between 12:00 and 16:00 a one-hour move changes views by less than 1%. For example, a post published on a Tuesday at 19:00 would typically have received 3.0% more views, 3.8% more likes and 2.9% more comments at 18:00, and 2.0%, 2.7% and 2.8% fewer at 20:00. The network term adds to this in markets whose latency varies within the day; in mature markets such as the United States it is a fraction of a percent.

When posts do best: engagement by local posting hour

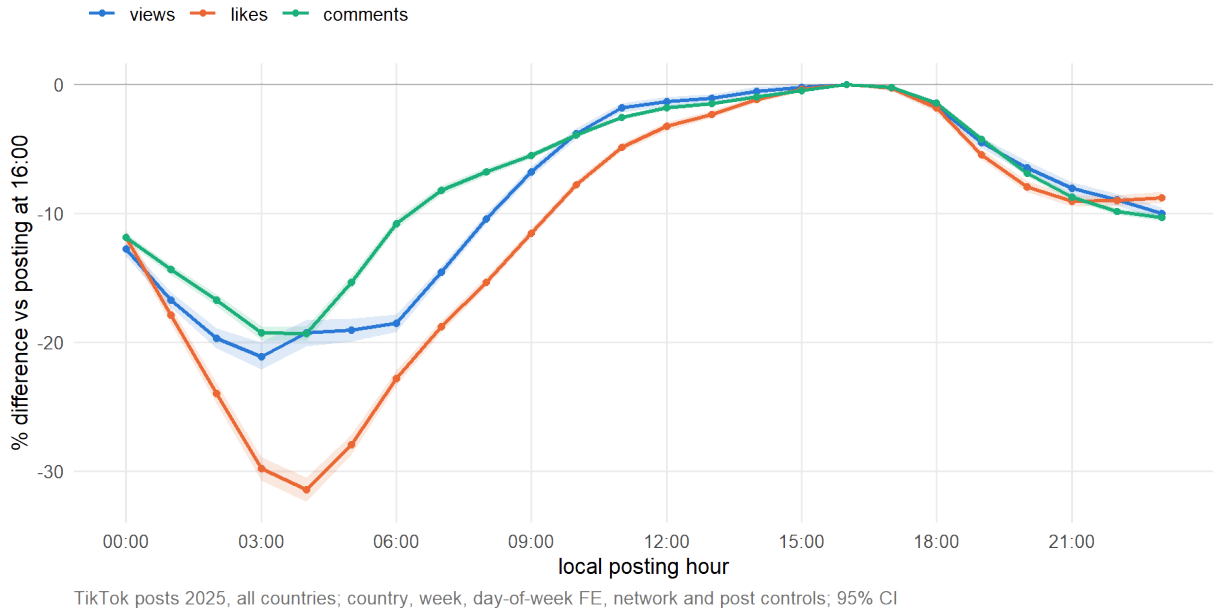


Figure 4: Engagement by local posting hour relative to 16:00, from model (1); 95% intervals.

5 Limitations

The estimates are associations, not experiments: the hour effects describe when posts typically do better (audience availability, competition, and which content is posted when), and the latency effect is identified from hour-to-hour network variation net of country, week, weekday and hour, which may still coincide with other events. The sample is dominated by posts tagged to the United States, and engagement is measured at one snapshot rather than at a fixed age. The network measure is national; the network a post’s first viewers used is not observed. We therefore present all numbers as typical effects with intervals, apply the latency effect only within ordinary ranges, and keep the network and timing components separate in any tool built on them.

6 Conclusion

Posting time matters through two channels. The audience channel is large and predictable: up to 20–30% between night and afternoon, about 3% for a one-hour move in the evening. The network channel is smaller but measurable: about 1% of views and comments per 10 ms of extra national latency, concentrated in markets whose networks vary. Both are now published as a single parameter set for KASPR’s post-timing check, which tells users, for any past post, what one or two hours earlier or later would typically have meant for views, likes, comments, shares and saves.

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Day of week matters less than hour of day

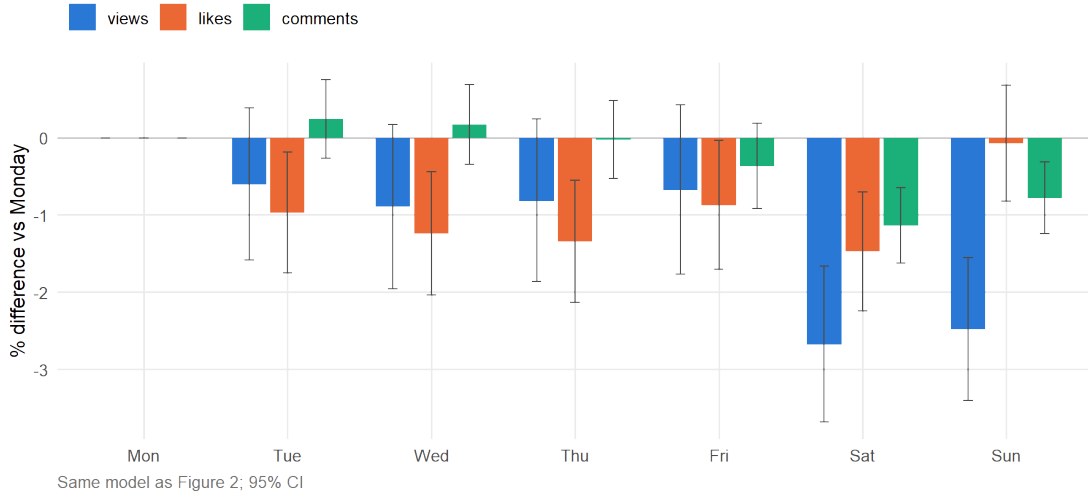


Figure 5: Engagement by local day of week relative to Monday; 95% intervals.

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What moving a post by an hour or two is typically worth (views)

actual posting time	00:00	+4.4%	+3.2%	-4.5%	-7.9%
	01:00	+8.0%	+4.7%	-3.6%	-5.3%
	02:00	+8.6%	+3.7%	-1.7%	+0.5%
	03:00	+5.6%	+1.8%	+2.3%	+2.6%
	04:00	-0.5%	-2.2%	+0.3%	+0.9%
	05:00	-2.5%	-0.3%	+0.6%	+5.5%
	06:00	-0.9%	-0.6%	+4.9%	+9.9%
	07:00	-5.2%	-4.6%	+4.8%	+9.1%
	08:00	-9.0%	-4.6%	+4.1%	+7.4%
	09:00	-8.3%	-3.9%	+3.2%	+5.4%
	10:00	-6.9%	-3.1%	+2.1%	+2.6%
	11:00	-5.1%	-2.0%	+0.5%	+0.7%
	12:00	-2.5%	-0.5%	+0.3%	+0.8%
	13:00	-0.7%	-0.3%	+0.6%	+0.9%
	14:00	-0.8%	-0.6%	+0.3%	+0.5%
	15:00	-0.9%	-0.3%	+0.2%	-0.1%
	16:00	-0.5%	-0.2%	-0.3%	-1.7%
	17:00	+0.1%	+0.3%	-1.4%	-4.2%
	18:00	+1.7%	+1.4%	-2.9%	-4.9%
	19:00	+4.4%	+3.0%	-2.0%	-3.7%
	20:00	+5.1%	+2.1%	-1.7%	-2.7%
	21:00	+3.9%	+1.7%	-1.0%	-2.1%
	22:00	+2.7%	+1.0%	-1.2%	-4.2%
	23:00	+2.2%	+1.2%	-3.1%	-7.4%
		-2 h	-1 h	+1 h	+2 h
		move the post by			

Hour-of-day part only (main model); a move across midnight also changes the day of week

Figure 6: Typical effect on views of moving a post by -2 to $+2$ hours, by actual posting hour (hour-of-day part of rule (2)).