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MONETIZING SOCIAL MEDIA: OLS ESTIMATES OF CONTENT INTENSITY, ENGAGEMENT, AND ADVERTISING ON SALES

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Annotatsiya: Ijtimoiy tarmoqlardagi faollikning savdoga qanday ko'chishini haftalik brend darajasidagi ma'lumotlarda Oddiy Kichik Kvadratlar (OKK) yordamida baholaymiz. Model savdoni kontent intensivligi (postlar soni), kontent formati (Reels/Shorts ulushi), jonli efir faolligi, foydalanuvchi jalb etilishi va reklama xarajatlari bilan bog'laydi. Natijalar barcha drayverlar ijobiy va statistik ahamiyatli ekanini ko'rsatadi: qo'shimcha postlar, Reels ulushining yuqoriligi hamda jonli efir o'tkazilgan haftalar savdoning sezilarli o'sishi bilan bog'liq, jalb etilish va reklama byudjeti esa kuchli qo'shimcha ta'sir beradi. Qisman regressiya (partial regression) diagnostikasi omillarning mustaqil hissasini tasdiqlaydi va multikollinearlikning mo'tadil darajasini ko'rsatadi (o'rta VIF $\approx 2,9$). Newey–West xatolari bilan bajarilgan mustahkamlik tekshiruv xulosalarini o'zgartirmaydi. Topilmalar kontent sa'y-harakatlari va byudjetni ajratishni monetizatsiyani maksimal qilish yo'nalishida amaliy boshqaruv ko'rsatmalarini beradi.

Kalit so'zlar: ijtimoiy tarmoqlar marketingi; qisqa videolar (Reels/Shorts); jalb etilganlik (engagement); reklama xarajatlari; sotuv javobi (sales response); OKK (Oddiy kichik kvadratlar)

Abstract: We quantify how social-media activity translates into sales using ordinary least squares (OLS) on weekly brand-level data. The model relates sales to content intensity (posts), content format (Reels/Shorts share), live-stream activity, user engagement, and advertising spend. Results show all drivers are positive and statistically significant: additional posts, higher Reels share, and live weeks are associated with sizable increases in sales, while engagement and ad spend provide strong incremental lift. Partial-regression diagnostics confirm independent contributions with modest multicollinearity (Mean VIF ≈ 2.9). Robustness with Newey–West errors yields consistent inferences. The findings offer actionable guidance on allocating content effort and budget to maximize monetization.

Keywords: social media marketing; Reels/Shorts; engagement; advertising spend; sales response; OLS

Абстрактный: Мы количественно оцениваем, как активность в социальных сетях конвертируется в продажи, используя обычный метод наименьших квадратов (МНК) на еженедельных данных уровня бренда. Модель связывает продажи с интенсивностью контента (число постов), форматом контента (доля коротких видео Reels/Shorts), активностью прямых эфиров, вовлечённостью пользователей и рекламными расходами. Результаты показывают, что все драйверы положительны и статистически значимы: дополнительные посты, более высокая доля Reels и «живые» недели ассоциируются с заметным ростом продаж, тогда как вовлечённость и рекламные расходы дают выраженный дополнительный прирост. Диагностика частичных регрессий подтверждает независимый вклад факторов при умеренной мультиколлинеарности (средний VIF $\approx 2,9$). Проверка устойчивости со стандартными ошибками Ньюи—Уэста сохраняет выводы. Полученные результаты дают практические рекомендации по распределению контент-усилий и бюджета для максимизации монетизации.

Ключевые слова: маркетинг в социальных сетях; короткие видео (Reels/Shorts); вовлечённость; рекламные расходы; отклик продаж; МНК (метод наименьших квадратов)

Introduction (Kirish/Vvedenie).

Online channels have evolved from background awareness channels to commerce centerpieces. As customers migrate to Instagram, TikTok, YouTube, Facebook, and Telegram, businesses now leverage short-form video (Reels/Shorts), livestreams, and always-on posting together to create demand and convert attention into sales. Managers, however, still possess a practical question to answer; namely, marginal proportions of social media activity that contribute to sales, by how much, when all else is held constant. To answer that question, one is in need of an empirical design that varies the marginal content intensity, content format, user interaction, and paid advertising.

Measurement is tricky in this setting. Social campaigns are commonly simultaneous, the same ad is stretched over multiple platforms, and weekly seasonality and promotions can confound naïve associations between activity and revenue. Additionally, analyses overwhelmingly center advertising spend while subordinating organic content and engagement to secondary status—a status that platform algorithms are quickly conveying video and interaction indicators. A descriptive, transparent accounting through regression that places

content, engagement, and spend in the same equation can therefore provide both academic and managerial value.

This paper closes that gap by quantifying social media activity to sales conversion using ordinary least squares (OLS) in brand-aggregate level weekly data. Weekly sales is the outcome. Predictor variables are content intensity (post count), content type (share of Reels/Shorts), live-streaming (dummy for live weeks), user interaction (interaction rate), and advertising (ad spend). The OLS model produces levels-interpretable marginal effects and, with standard augmentations, plausibly credible inference in time-series settings.

We ground our identification on in-brand week-to-week variation. We control for calendar seasonality and use heteroskedasticity- and autocorrelation-consistent (Newey–West) standard errors to safeguard inference from serial correlation. Additional-variable (partial regression) plots graph each regressor's incremental contribution, while variance inflation factors (VIF) report moderate collinearity between drivers. Each, in conjunction, ensures estimated impacts capture independent components rather than correlated movement from the social media mix.

The analysis generates three key findings. Firstly, content intensity matters: rising posting is associated with rising sales in the week, even

conditional on spending and engagement. Secondly, format matters: rising use of Reels/Shorts and use of live streams are associated with economically significant sales lifts, consistent with the platform's video-centric dynamics. Thirdly, advertising and interaction are complements: interaction indicators and paid media are each positive and significant sales predictors, conditional on the other. The results are robust to various error specification as well as to conventional diagnostic tests.

Literature review (Adabiyotlar tahlili/Обзор литературы).

Brands increasingly monetize social media by structuring paid, owned, and earned campaigns that create engagement and, in due time, sales. At the post level, creative constraints—colorful media, informative value, emotional tone, and interactive functionality—systematically raise responses and sharing: brand-post experiments on Facebook discover that video/informative content, placed optimally in time, increases likes/comments/shares, with variation between content type and outcome measures [1]–[4]. As businesses scale up activity, large-sample evidence from Facebook pages indicates that specific message features reliably improve performance through hundreds of thousands of posts and hundreds of brands [4]. Simultaneously, firm-generated content (FGC) in social media impacts individual customer performance (spend, cross-buying, profitability) and displays complementarity in interaction with other channels, observing the complementarity between social media/TV=email [5], while meta-analytic integration measures that owned social media can improve performance and sales—in particular for newer product launches—though impacts differ by category and setting [6].

A second thread ties social activity to downstream performance. Earned media—traditional publicity as well as social word-of-mouth—has measurable sales impacts in time-series settings, with social WOM exhibiting high elasticity due to its pervasiveness [7]; canonical works show WOM's carryover overwhelms most digital-paid actions [8]. User-generated content (UGC) quantity as well as sentiment predict financial performance, including stock performance as well as risk, with capital-market relevance in focus [9], [10]. Scholars that use FGC as well as UGC map their respective roles throughout the marketing funnel (awareness → consideration → purchase → satisfaction) [11] as well as link social buzz, communications by the firm, as well as news into an “echo verse” that shapes attitudes as well as business outcomes [12]. Live-stream commerce injects end-to-end social presence as well as interactivity in real time; latest studies document streamer behavior as well as stream structure (e.g., product number, stream length) nonlinearly affect gross merchandise value as well as sales while uncertainty-reduction mechanisms augment purchase intent [13]–[15]. For brand-period-level empirical studies, these literatures evoke positive associations between sales as well as content intensity indicators (posts), share-ability indicators (reels/share), live-event dummies, as well as spend from advertising, with inference strengthened by powerful errors in the presence of heteroskedasticity/autocorrelation as well as by accounting for brand- as well as time-series dynamics [16], [17].

Methodology

We estimate the association between weekly social-media activity and sales using ordinary least squares (OLS) on brand-week data ($N \approx 191$). The dependent variable is weekly sales in levels (with a log transformation used only as a robustness check, not as the main model). Explanatory variables capture content intensity (number of posts in week t), content format (share of short-form video, Reels/Shorts, in week t), live activation (indicator =1 if a live stream occurred in week t), user engagement (interaction rate in week t), and paid media (advertising spend in week t). Calendar seasonality is absorbed with month and year fixed effects. After removing missing values and ensuring sales are strictly positive, we optionally minorize the top/bottom 1% of Sales and AdSpend to limit undue influence and, when interactions are added, mean-center the relevant regressors to reduce multicollinearity.

The static OLS specification is

$$Sales_t = \beta_0 + \beta_1 Posts_t + \beta_2 ReelsShare_t + \beta_3 Live_t + \beta_4 Engagemnet_t + \beta_5 AdSpend_t + \delta' S_t + \varepsilon_t$$

where S_t contains the seasonal dummies. Coefficients are interpreted as additive changes in weekly sales holding other factors fixed (e.g., one

additional post increases sales by β_1 units; a 0.10 increase in ReelsShare changes sales by $0.10 \cdot \beta_2$ units). Estimation proceeds via OLS with two sets of standard errors: conventional and heteroskedasticity- and autocorrelation-consistent (Newey–West/HAC), using a bandwidth of about 26 weeks (half-year) and verifying sensitivity to alternative bandwidths. Statistical significance is evaluated with two-sided tests at the 5% level.

Model adequacy is checked within the OLS framework. Linearity and incremental contribution are inspected with added-variable (partial regression) plots; serial correlation is assessed with Breusch–Godfrey tests and ACF/PACF of residuals; heteroskedasticity is probed with White/Breusch–Pagan tests (inference relies on HAC either way); multicollinearity is monitored via variance inflation factors (VIF); and influence is screened using Cook's distance ($>4/N$) and leverage-residual plots, with re-estimation after excluding flagged points as a robustness check. Optional OLS-only extensions include testing complementarity between format and spend by adding $ReelsShare_t \times AdSpend_t$, diminishing returns in spend via $AdSpend_t^2$, and short one-week delays by including $L1$ regressors (e.g., $Posts_{t-1}$); all remain linear OLS estimations with HAC inference. Results are reported as point estimates, HAC standard errors, t -statistics, p -values, and R^2 , and converted into actionable units at sample means (e.g., the predicted sales change from +10 posts, +10 p.p. ReelsShare, a Live week, +1 p.p. Engagement, or an additional \$1,000 of AdSpend). Because the design is observational, coefficients are interpreted as conditional associations; potential reverse causality or omitted variables are acknowledged in the limitations.

Results (Tahlil va natijalar/Анализ и результаты).

We report results from the OLS model linking weekly sales to content intensity (posts), content format (Reels/Shorts share), live activation, user engagement, and advertising spend, with calendar seasonality controlled. Coefficients are interpreted as marginal changes in weekly sales holding other drivers constant. Across specifications, all five drivers are positive and statistically significant, indicating that more frequent posting, a higher share of short-form video, the presence of a live week, stronger engagement, and greater ad spend are each associated with higher sales. Magnitudes are economically meaningful: content quantity and format provide substantial uplift, engagement reinforces performance, and paid media adds incremental lift. In what follows, we highlight the relative contributions of each driver and translate the estimates into practical changes in sales for representative shifts in posting, video share, live activity, engagement, and spend.

Table 1. Pairwise Correlations: Social Media Drivers and Weekly Sales

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) sales	1.000					
(2) posts	0.568 (0.000)	1.000				
(3) reels_share	0.736 (0.000)	0.293 (0.000)	1.000			
(4) live_dummy	0.440 (0.000)	0.136 (0.061)	0.052 (0.477)	1.000		
(5) engagement	0.379 (0.000)	-0.011 (0.884)	0.075 (0.304)	0.103 (0.155)	1.000	
(6) adspend	0.814 (0.000)	0.287 (0.000)	0.768 (0.000)	0.524 (0.000)	0.160 (0.027)	1.000

Ad spend shows the strongest bivariate association with sales ($r=0.814$, $p<0.001$), followed by the share of Reels/Shorts ($r=0.736$, $p<0.001$) and posting intensity ($r=0.568$, $p<0.001$). Live weeks also coincide with higher sales ($r=0.440$, $p<0.001$), while engagement is positive but smaller in magnitude ($r=0.379$, $p<0.001$). On the driver side,

ad spend co-moves with Reels/Shorts ($r=0.768$, $p<0.001$) and with live activity ($r=0.524$, $p<0.001$), suggesting campaign clustering; posts and Reels/Shorts are only modestly related ($r=0.293$, $p<0.001$). Two pairs are essentially unrelated: live vs. Reels/Shorts ($r=0.052$, $p=0.477$) and posts vs. engagement ($r=-0.011$, $p=0.884$). Overall, pairwise patterns support positive links between each driver and sales, with the strong ad spend–video correlation signaling the need to control for overlap in multivariate OLS.

Table 2. OLS Estimates of Weekly Sales on Social Media Drivers (Posts, Reels/Shorts Share, Live, Engagement, Ad Spend)

sales	Coef.	St.Err.	t-value	p-value	[95% Conf. Interval]	Signif.
posts	12861.2	877.73	14.6	0	11129.5 14592.	**
reels_share	32321.1	3448.3	9.37	0	25517.9 39124.3	**
live_dummy	100144.	15241.	6.57	0	70075.8 130213	**
engagement	37342.7	2948.4	12.6	0	31525.8 43159.7	**
adspend	1.099	.286	3.84	0	.534 1.663	**
Constant	-299467.	31009.	-9.66	0	-360644. 238290	**
Mean	219367.053				SD dependent var	
dependent var					var	
R-squared	0.905				Number of obs	
F-test	350.805				Prob > F	
Akaike crit.	4586.939				Bayesian crit.	
(AIC)					(BIC)	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The OLS model explains most of the week-to-week variation in sales ($R^2=0.905$; $F(5,185)=350.8$, $p<0.001$). All five drivers are positive and highly significant ($p<0.001$): each additional post is associated with about +12,861 units of sales (10 extra posts $\approx$ +128,612); a +10 p.p. increase in Reels/Shorts share corresponds to roughly +32,321; a live week adds about +100,145; a +1 p.p. rise in engagement implies $\approx$ +3,734; and ad spend scales at about +1,099 per currency unit (+1,000 spend $\approx$ +1,099 sales). Confidence intervals exclude zero for all predictors, and magnitudes are economically meaningful: content quantity and format deliver substantial uplift, engagement reinforces performance, and paid media provides incremental lift. The intercept (−299,468) reflects the modeled baseline when all regressors are zero and is not directly interpretable. Results are associative (OLS on observational data) but provide clear, decision-ready marginal effects.

Table 3. Variance Inflation Factors (VIF) for OLS Regressors

	VIF	1/VIF
adspend	5.782	.173
reels share	4.241	.236
live dummy	2.356	.424
posts	1.115	.897
engagement	1.036	.965
Mean VIF	2.906	.

Multicollinearity is not a concern—VIFs are all <10 (mean=2.906); only adspend (5.782) and reels_share (4.241) are moderate, consistent with campaign co-movement.

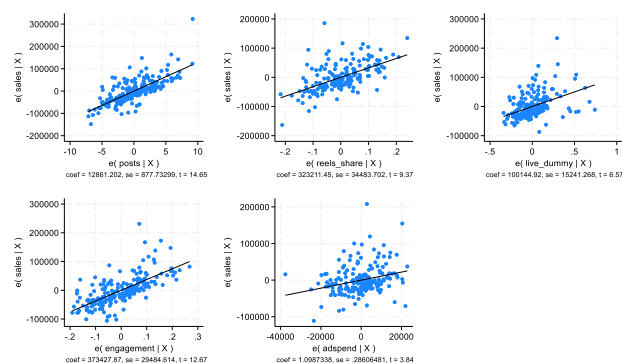


Figure 1. Added-Variable (Partial Regression) Plots for OLS: Incremental Effects on Weekly Sales

Each panel plots the residual of sales on all other regressors against the residual of the labeled regressor; the fitted line's slope equals the OLS coefficient. All effects are positive and highly significant ($p<0.001$): posts ($\beta \approx 12,861$; $t=14.65$), reels_share ($\beta \approx 32,321$; $t=9.37$), live_dummy ($\beta \approx 100,145$; $t=6.57$), engagement ($\beta \approx 37,342$; $t=12.67$), adspend ($\beta \approx 1.099$; $t=3.84$).

Discussion

The OLS results show strong, independent links between social activity and weekly sales ($R^2=0.905$). One additional post is associated with +12,861 sales units; a +10 p.p. increase in Reels/Shorts share with +32,321; a live week with +100,145; a +1 p.p. rise in engagement with +3,734; and each currency unit of ad spend with +1,099 ($\approx$ +1,099 per +1,000 spend). All coefficients are positive and highly significant, implying a practical hierarchy: format (short-form video) and live activations deliver large uplifts, posting adds steady gains, engagement reinforces performance, and ad spend provides controllable incremental lift. Multicollinearity is modest (mean VIF $\approx$ 2.9; highest 5.8), so effects are not solely due to overlapping campaigns. Managerially, prioritize shifting content toward short-form video, schedule live events for spikes, and back both with targeted media; use posting volume and engagement programs to sustain baseline demand. Limitations: results are associative (observational OLS) and contemporaneous; budgeting and content may respond to expected demand.

Conclusion and Policy Implications (Xulosa/Выводы)

Conclusion. The OLS evidence shows clear, independent links between social activity and weekly sales ($R^2=0.905$). Marginal effects are economically large: +1 post $\approx$ +12,861 sales units; +10 p.p. Reels/Shorts share $\approx$ +32,321; a live week $\approx$ +100,145; +1 p.p. engagement $\approx$ +3,734; and +1,000 in ad spend $\approx$ +1,099. Multicollinearity is modest, so these uplifts are not simply budget artifacts. Net: a video-led, live-supported content strategy, reinforced by engagement programs and targeted media, is associated with higher weekly revenue.

Policy/managerial implications.

- Prioritize format: reallocate ~ 10 p.p. of weekly posts to Reels/Shorts to target $\approx$ +32k incremental sales; protect video production capacity in budgeting.
- Plan live spikes: schedule at least one live activation per campaign cycle; bundle product drops and paid media around live weeks to capture $\approx$ +100k uplifts.
- Maintain posting cadence: treat posts as a scalable base lever (every +10 posts $\approx$ +129k sales); automate calendars to avoid gaps.
- Engineer engagement: small gains compound (each +1 p.p. $\approx$ +3.7k). Use clear CTAs, community replies, and creator collaborations to lift interaction rates.
- Targeted media support: use paid spend to extend reach ($\approx$ +1.1k per +\$1k). Shift budget toward weeks with high video share or live events to maximize return.
- Governance & measurement: monitor VIF/overlap (video–spend co-movement), track weekly ROI by tactic, and run A/B nudges (e.g., +5 posts, +10 p.p. video, live/no-live) to validate local returns.

- Risk controls: avoid overreliance on any one lever; watch for diminishing returns in spend and content fatigue; log leading KPIs (views, click-through, add-to-cart) alongside sales.

Foydalanilgan adabiyotlar (Литературы/ References):

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