Show Me The Money, Sooner! How Faster Payments Boost Gig Workers' Efforts and Productivity

Shiyi Wang
Nanyang Technological University, shiyi001@e.ntu.edu.sg

Jack Tong
Nanyang Technological University, jack.tong@ntu.edu.sg

Nan Jia
University of Southern California, Nan.Jia@marshall.usc.edu

Show Me The Money, Sooner! How Faster Payments Boost Gig Workers' Efforts and Productivity

Completed Research Paper

Shiyi Wang
Nanyang Technological University
50 Nanyang Avenue, Singapore 639798
shiyi001@e.ntu.edu.sg

Jack Tong
Nanyang Technological University
50 Nanyang Avenue, Singapore 639798
jack.tong@ntu.edu.sg

Nan Jia
University of Southern California
Los Angeles, California 90089
nan.Jia@marshall.usc.edu

Abstract

Despite their astounding growth in recent years, online gig platforms face key challenges to increase gig workers' working commitment. This study aims to examine the impact of a fundamental organizational design element payout frequency, which refers to the intervals at which workers access the funds they have earned. Drawing on expectancy theory, we argue that a higher payout frequency enhances both the quantity and quality of gig work. To investigate this, we analyze proprietary data from a quasi-natural experiment that involved an unexpected reduction in the payout cycle for gig workers in a specific geographic region. By employing propensity score matching and a difference-in-differences approach, we demonstrate that a shorter payout cycle led to an increase in the effort among the impacted gig workers and also resulted in improved work quality. These findings contribute to our understanding of effectively motivating and managing gig workers, ultimately influencing customer engagement on platforms.

Keywords: Template, formats, instructions, length, conference publications

Introduction

The "gig economy," defined as online labor markets for independent and flexible contracting (Burtch et al. 2018; Greenwood et al. 2017; Woodcock and Graham 2019), has been growing exponentially in recent years around the globe (Ai et al. 2023; Rahman and Valentine 2021). A recent survey in 2022 showed that a staggering 39% of the US workforce (i.e., around 60 million Americans) participated in at least one type of freelance work in the past 12 months through online gig platforms such as Airbnb, Upwork, Deliveroo, Uber, and Twitch.[1] Furthermore, the global gig workforce is predicted to grow to 78 million and the payout disbursement will reach USD 298 billion by 2023.[2]

Despite their astounding growth in number and prominence, gig platforms increasingly face the challenges of retaining gig workers and motivating them to deliver high-quality work (Carnahan et al. 2017; Wong 2022; Wu et al. 2019). Indeed, constrained by the flexible labor contracts with gig workers, gig platforms

1 https://www.upwork.com/research/freelance-forward-2022

2 https://www.mastercard.us/content/dam/public/mastercardcom/na/us/en/documents/mastercard-fueling-the-globalgigeconomy-2020.pdf

are unable to use many traditional human resource management practices, such as career programs, team building, or workplace training, to engage with and motivate gig workers (Farrell and Greig 2016; Jabagi et al. 2019; Wong et al. 2021). Moreover, the lack of traditional organizational scaffolds in gig work can undermine workers' intrinsic motivations (Cameron 2022). Furthermore, competition among gig platforms for workers has intensified over time, exacerbating turnovers (Johnston and Land-Kazlauskas 2018; Vallas and Schor 2020; Wood et al. 2019). Thus, lacking abilities to tackle these challenges could substantially undermine a platform's profitability and long-term growth (Akhtar 2019; Burbano and Chiles 2022; Cao et al. 2022).

A growing number of anecdotes show that gig platforms are trying to leverage a simple organizational design—a shorter payout cycle that enables them to clear payments for gig workers at a higher frequency, to increase workers' motivation. For example, upon popular request of drivers, both Lyft and Uber have launched express payout features that enable real-time payout such that drivers have instantaneous access to the money they have earned (Bhuiyan 2016; Etherington 2017). To address hosts' complaints about late or missing payments, Airbnb introduced the *FastPay* feature for hosts in the US in early 2022, which reduced the payout processing time from a few business days to a few hours (Mehta 2022). Indeed, some mainstream gig platforms have adopted payout cycles that are much shorter than conventional biweekly or monthly payout cycles that existed at traditional organizations in the U.S..[3]

However, there exists a limited theoretical understanding and no empirical evidence showing whether a shorter payout cycle indeed increases gig workers' work commitment and improves the work quality delivered on the platform—or on what types of workers this change produces larger effects (Burtch et al. 2022; Conroy et al. 2022). Prior research has mostly focused on how the amount or structure of payment (such as wages and bonuses) shape the commitment and performance of employees in traditional organizations (Benson and Sajjadiani 2018; Gallus et al. 2023; Gerhart et al. 2003; MacLeod and Malcomson 1998; Nyberg et al. 2016). In particular, the more frequent payout increases employees' financial liquidity (Baugh and Correia 2022), improves their perception of own wealth and reduces mental burden about financial concerns, thus lifting employees' work motivation (De La Rosa et al. 2022; Kaur et al. 2021). On the contrary, in the context of the gig economy, elevated levels of financial liquidity and perception of wealth could be detrimental to gig workers' motivation. A primary reason people engage in gig work is to earn supplemental income to meet the financial needs that their primary incomes cannot satisfy (Anderson et al. 2021); for example, a recent survey demonstrates that around 44% of Americans are working at least one gig job for the purpose of making ends meet each month (Reinicke 2022; Smith 2022). Nevertheless, improved liquidity and perception of wealth will lead gig workers to conclude that they have earned enough supplemental income to meet their financial objectives, resulting in a reduction in the amount of effort they put into gig work. Thus, theoretically, it is unclear whether gig platforms should implement a shorter payout cycle for the goal of increasing gig workers' efforts and performance, despite the popularity of such practices on gig platforms.

To address this tension, we draw on the expectancy theory, a common lens through which to understand how individuals are motivated by a stimulus, to analyze how payout cycles shape gig workers' behaviors at work. According to the expectancy theory, three main channels influence individual behaviors: expectancy (the belief that one's efforts could lead to desired goals), instrumentality (the belief that that meeting performance expectations will result in rewards), and valence (the value of the rewards) (Campbell and Pritchard 1976; Friedman et al. 2008; Gatewood et al. 2002; Vroom 1964). Prior studies have found that organizations can enhance employees' work motivation and commitment by designing incentive schemes that increase any of these three components(Campbell and Pritchard 1976; Oliver 1974; Renko et al. 2012). Building on this literature, research indicates that employees' reward expectancy is influenced by a variety of factors related to individuals' psychological and cognitive aspects (Chiang and Jang 2008; Schunk 1991; Vroom 1964). In particular, a shorter payout cycle enables gig workers to collect their earnings more frequently, thus producing more recurrent stimuli to reinforce workers' perception about the connection between expending efforts and attainment of desired goals (thus higher expectancy) and the likelihood of being rewarded for the performance (thus higher instrumentality). Therefore, a shorter payout cycle should increase gig workers' motivation at work (Chiang and Jang 2008; Oliver 1974; Renko et al. 2012).

3 https://www.dol.gov/agencies/whd/state/payday/history

To empirically examine our hypotheses, we collaborated with a social voice-streaming app (the "platform" hereafter, as the company prefers to be anonymous) headquartered in Singapore, with business operations in South Asia and North Africa. The platform hosts individual voice streamers to set up chat rooms and interact with audiences in their chat rooms. Streamers provide services including streaming content and interacting with audiences, and they receive payment in the form of virtual gifts from the audience. The platform works with local finance settlement vendors in each region to collect online payments from audiences who purchase virtual gifts and distribute payouts to the streamers who receive these gifts on a monthly basis across all regions. On June 1, 2022, the platform changed the payout cycle for streamers in the South Asia region from 30 days to 10 days as a result of an unexpected upgrade of a local finance vendor's settlement system, while the payout cycles in other regions remained unchanged. Using the platform's proprietary data, we construct a dataset at the level of the individual streamer by each payout period (i.e., every 10 days for streamers in South Asia after the shock) from March to August 2022 (i.e., three months before and three months after the shock).

Adopting a propensity score matching (PSM) method and a difference-in-differences (DID) approach with two-way fixed effects (Flammer and Kacperczyk 2016; Qian et al. 2019; Singh and Agrawal 2011; Younge et al. 2015), we generate several interesting findings. First, a shorter payout cycle indeed significantly increased streamers' efforts: On average, streamers given a shorter payout cycle produced 30.7% more streaming sessions, and the total streaming duration increased by 80.9%. Second, a shorter payout cycle improved the quality of streaming services: streamers in the treatment group attracted 34.2% more listeners and received 220.6% higher total gift value during an average 10-day period. At a finer-grained level (i.e., individual streaming sessions), streamers in the treatment group attracted 10.3% more listeners, 7.9% more listeners sent them virtual gifts, and the total gift value they received increased by 150.4%. These results suggest that the streamers in the treatment group were rewarded by the audience to a greater extent, reflecting that they produced higher-quality streaming content for the audience. Third, such positive impacts of a shorter payout cycle on streamers' efforts and streaming quality are heterogeneous based on streamers' capabilities to attain the performance incentives and work commitment to the platform.

This research makes multiple contributions. First, we provide a theoretical basis and the first empirical evidence showing that payout cycle design is a pivotal tool for gig platforms to motivate gig workers to exert greater efforts on the platform. This insight fills the gap left by the difficulties of grafting the extant theory developed on motivating employees in traditional organizations to understand how payout cycles affect gig workers. Moreover, our results show that a shorter payout cycle improves the quality of the work delivered by gig workers, measured by customer engagement and satisfaction, which are particularly important for gig platforms.[4] Gig platforms thrive on customer satisfaction which contributes to their reputation and strengthens their competitive edge (Benson et al. 2020). However, most gig platforms have limited access to conventional human resource practices to exert quality control on the work produced by gig workers. Our study demonstrates that shortening the payout cycle, even without offering additional monetized incentives, produces a sizable improvement in gig workers' quality of work. Furthermore, this study also shows that a shorter payout cycle also benefits gig workers, by increasing their efforts that lead to higher rewards captured by themselves (higher total value of gifts received). Finally, these insights are much needed as many gig platforms contemplate shortening their payout cycles to tackle the challenges of motivating gig workers to exert greater efforts (Magloff 2022; Mint 2022) but need to ascertain whether such practices can indeed achieve the intended goals.

Empirical Setting and Data

The Platform

The platform is a social voice streaming app that hosts individual voice streamers to share their personal stories, showcase their talents, and build relationships with audience (e.g., in our empirical context, we use "listeners" hereafter) by setting up audio chat rooms (akin to a personal radio station) to communicate with the audience anytime and anywhere. These streamers can be appropriately called gig workers because they operate as independent contractors within the gig economy model (Bulletin 2022; Qu 2021). They are not employees of the platform but utilize it as a means to provide their services to customers (listeners). Their

4 In our empirical context, gig platform customers are individual audience in live streaming rooms.

work is based on flexible arrangements and they earn income through virtual gifts. The platform was founded in Singapore in December 2020. It first started to operate in South Asia (Bangladesh, Pakistan, and India) and North Africa (the Arabic-speaking countries including Egypt, Morocco, and Sudan), and later expanded its presence to Southeast Asia (Thailand and Indonesia) and South America (Brazil). Listeners in these regions download the platform app from Google Play, Apple Store, and other third-party app markets. As of November 2022, the platform had attracted over 750,000 app downloads and accommodated around 10,000 streamers to set up chat rooms. Streamers on the platform are from diverse professional backgrounds; they include working professionals, university students, homemakers, and government employees. Most streamers host virtual chat rooms in their spare time to showcase their talents such as storytelling and singing and share stories about their lives.

Listeners logging in to the platform can explore and navigate individual live chat rooms, by selecting from the recommended list on the landing page or using the ”Category” tab in the top section of the landing page to choose their preference or interest (an example is provided in the left panel of Figure1). Listeners can enter any live chat room by simply clicking the room icon, and they can also leave the room at any time. The right panel of Figure1 provides a screenshot of the interface of an individual chat room. In this figure, the top section displays the chat room name and ID with a list of the most popular chat rooms in the same category. The middle section of the chat room displays the name and icon of each listener currently in the room. Although listeners cannot directly talk with the streamer (the chat room host) or other listeners, they can request the streamer to speak in the chat room through chats. Listeners can also send text messages to everyone in the chat room by typing in the bottom-left column. Finally, listeners can purchase and send virtual gifts to streamers of their choice to show their appreciation.

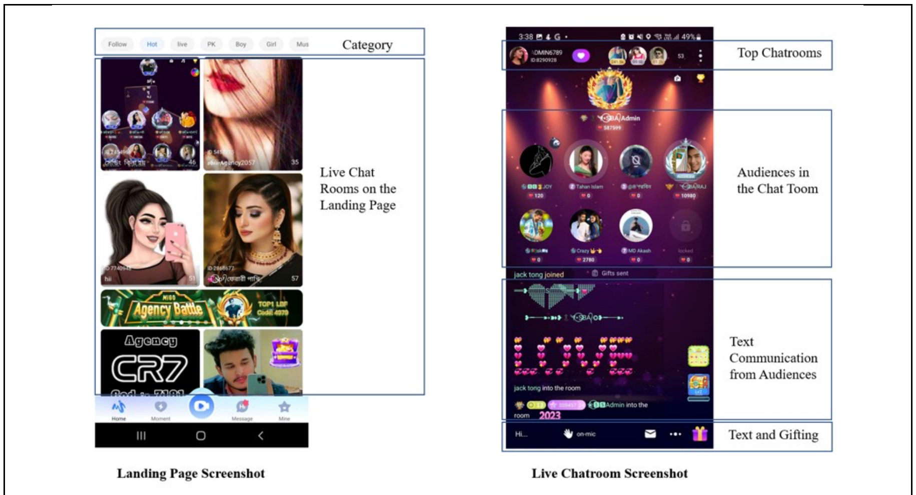

Figure 1. Screenshot of the Landing Page and Live Chat Room

Virtual gifts on the platform are eligible for purchase only with the virtual currency designed by the platform. On average, 1,000 units of virtual currency are equivalent to one USD dollar. Listeners can use their bank cards or credit cards to top up the virtual currency and then use this currency for virtual gift purchases in the app. Streamers can redeem virtual gifts they have received in the local currency, which constitutes the payout to them.[5]

In order to process transactions of virtual currency top-ups by listeners and virtual gift redemption by streamers in local regions, the platform collaborates with several local financial settlement vendors. Each vendor provides a payment interface that enables listeners to charge bank cards or credit cards in their local currency to top up the platform's virtual currency. Once vendors receive the online payment from listeners, they wire the amount to the platform's local bank account. Every month, the platform redeems all virtual

5 The platform charges a 30% service fee for redemption; this rate remains the same in all regions.

gifts in the streamers' account given in the previous month and wires the amount in local currency through financial vendors to the streamers' bank account at the beginning of the following month automatically.

Exogenous Shock of Payout Cycle Change

In May 2022, the vendor handling the platform's online payment in South Asia upgraded to a new financial settlement system with the support of an investment from an external institutional investor. This new system allowed the vendor to consolidate online purchase funds and distribute the redemption funds more efficiently (i.e., it reduced the handling time from more than one week to less than 48 hours). As a result, this upgrade unexpectedly facilitated the platform to shorten the payout cycle for streamers in South Asia from 30 days to 10 days. The policy change occurred on June 1, 2022, for all streamers in South Asia region whereas the gift redemption and payout cycle for streamers in other regions remained unchanged.

It is highly plausible that this unexpected policy change provides an exogenous context for us to identify the causal impact of a shorter payout cycle on gig workers' performance for the following reasons. First, the upgrade decision of the local vendor is based on the receipt of external investment support unrelated to our focal platform. The vendor is a major financial service provider in South Asia for many business-tocustomer online platforms, and thus it is highly unlikely that the vendor received the external investment because of the business performance of our focal platform (e.g., ruling out reverse causality concern).

Second, the policy change was communicated through both in-platform messages and emails to streamers in the affected region on the day of the policy change. Streamers in other regions were not informed and were likely to stay unaware of the payout cycle change in South Asia because of geographical distance and language barriers. Third, the management confirmed to us that the revamp of the payout cycle did not affect any front-end interface feature between streamers and the audience. Thus, streamers in the South Asia region interact and engage with the audience in the same way as they did before and as streams did in other regions. Fourth, very few streamers would choose a registration country different from their home country. Therefore, streamers are not self-selected to create an account in South Asia in response to the payout cycle change. Finally, during the period of our data collection (i.e., from March 2022 to August 2022), there are no other promotions on the platform that may impact streamers' efforts or performance.

Data

To understand how the payout cycle change affected streamers' efforts and performance quality, we acquire proprietary data from the platform on streamers' streaming activities in both South Asia and North Africa regions, the two largest markets for the platform. The original dataset contains detailed records for each voice streaming session, including the streamer ID, streaming duration, number of listeners, entry and exit time stamps of each listener, user IDs of listeners who sent virtual gifts during the streaming session, and the value of each virtual gift. The dataset spanned six months from March to August 2022 (i.e, three months before and three months after the change to the payout cycle).

The platform removed sensitive personal information, including identity streamers and listeners. Second, they aggregated individual streamers' streaming activities, audience participation, and gifting behaviors in the chat room to the time interval of every 10 days (the new payout cycle) for our main analyses. Third, they removed the information of streamers whose streaming sessions and virtual gifts were above three standard deviations from the mean value of the sample (which were rare). They also omitted streamers who had less than three months of history of working on the platform prior to the change to payout. Thus, the final dataset includes a total of 3,711 individual streamers and 66,798 observations over six months. More details of the country distribution are shown in Table1.

Country/Region	No. of Streamers	No. of Observations
North Africa (Egypt, Morocco, and Sudan)	767	13,806
Bangladesh (South Asia)	2,255	40,590
Pakistan (South Asia)	260	4,680
India (South Asia)	429	7,722

Total	3,711	66,798

Table 1. Sample Composition by Region

Identification Strategy

To alleviate concerns over endogeneity issues, we combine the PSM and a DID approach with the two-way fixed effects. First, we construct the control group with streamers in the North Africa region who were not exposed to this policy change during our observation period. In our main analyses, we use streamers in Bangladesh as the treatment group for the following reasons. First, Bangladesh had the largest number of streamers in our sample, which would provide higher statistical power for analyses (details shown in Table2).6 Second, Bangladesh's GDP per capita (USD 2,500) is closest to that of the North Africa region (USD 3,500–4,000), suggesting a more-similar wealth level.7 Lastly, both the North Africa region and Bangladesh have a large, dominant Muslim population (89% of the population in Bangladesh and around 90%–95% in the North Africa region), indicating similar religious backgrounds. 8 We also test the robustness of the results using streamers in India and Pakistan as the treatment group.

We construct matching samples of streamers in the treatment group to those in the control group based on demographic information including age, gender, and tenure on the platform, as well as pre-experiment streaming activities, including the number of streaming sessions, streaming duration, audience size, and the value of virtual gifts received.9 We adopt a 1:3 nearest-neighbor matching method with the replacement for the matching procedure. The matched outcomes are summarized in Table2. Indeed, despite notable differences between streamers in the treatment and unmatched control groups, and the matching process significantly reduces the difference across observed covariates.

Variable	U/M	Mean		t-test	
		Treated	Control	t	p-value
Male	U	0.293	0.566	-14.000	0.000
	M	0.517	0.498	0.800	0.425
Tenure (Days on the platform)	U	262.000	265.440	-1.820	0.069
	M	267.330	265.520	0.790	0.430
Age	U	23.824	27.952	-14.940	0.000
	M	26.266	26.292	-0.060	0.951
Total Number of Streaming Sessions	U	9.332	3.637	11.590	0.000
	M	4.241	3.788	1.220	0.222
Total Duration of Streaming Sessions (minutes)	U	364.110	125.760	12.590	0.000
	M	141.380	133.060	0.660	0.511
Audience Size	U	24.176	10.915	6.730	0.000
	M	12.588	11.754	0.490	0.622
Total Value of Virtual Gifts (Virtual Currency)	U	50097.000	25609.000	5.370	0.000
	M	25334.000	26077.000	-0.170	0.865

6 Because the control group has a relatively small sample size, the statistical power of the analysis will not change if we include the streamers in Pakistan and India as treatment groups.

7 The GDP per capita for Pakistan and India were USD 1,500 and USD 2,200, respectively. https://data.worldbank.org/

8 https://www.state.gov/reports/2021-report-on-international-religious-freedom/

9 Measures of streaming activities are averaged on a 10-day interval for each streamer across the three-month pre-treatment period.

Note. N = 2424. Control = 606. Treat = 1818. U = unmatched data. M = matched data.
Table 2. PSM Matching Balance Check

Next, we leverage the matched panel data to construct a DID model with two-way fixed effects to address concerns over unobserved endogeneity. We include the individual streamer fixed effects to account for any individual-specific, time-invariant unobserved factors (such as personality, the talent of streaming, and education level). We also control for unobserved common time trends across all individuals (such as seasonality, holidays, and weekend) by including time-fixed effects. Our DID model specification is listed in Equation1.

$$\boldsymbol{Y_{it}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 Post_t} \times \boldsymbol{Treat_i} + \boldsymbol{\theta_t} + \boldsymbol{\lambda_i} + \boldsymbol{\epsilon_{it}} \text{ } (\textbf{Equation 1})$$

Here, the dependent variable Y_{it} refers to variables measuring streamer i's streaming efforts and performance during the given time interval t. $Treat_i$ is a binary indicator that equals 1 if streamer i is in the treatment group and equals 0 otherwise. $Post_t$ is a time-varying indicator that equals 1 if the observed time interval is after the payout cycle revamp date (June 1, 2022). Our estimation interest is the value of α_1, which gauges the intertemporal variation in streamers' streaming activities and performance between the treated and control groups before and after the payout cycle revamp. It is noted that the main effects of $Treat_i$ and $Post_t$ are subsumed by the two-way fixed effects in the model. θ_t accounts for time-fixed effects and λ_i captures the individual fixed effects. ϵ_{it} refers to heteroskedasticity-robust standard errors clustered on the individual streamer level.

Analyses and Findings

Impact of Payout Cycle on Streamers' Effort

To examine the impact of a shorter payout cycle on streamers' streaming efforts, we estimate Equation1 with dependent variables that measure streamers' efforts. The number of streaming sessions and length of streaming sessions are common indicators of streamers' efforts expended on the given platform (Zeng et al. 2020). Thus, we adopt the measurements of total streaming sessions, total duration of streaming, and average streaming duration.

Table3 reports the estimation results. First, the positive coefficients of the interaction term of interest ($p< 0.001$) in columns (1) and (2) show that a shorter payout cycle drove streamers to offer more streaming sessions. The coefficient estimation in column (1) suggests that streamers in the treatment group on average produced 2.508 more streaming sessions in a 10-day period than those in the control group. Because the dependent variable in column (2) has been log-transformed, the coefficient estimate suggests that the reduction of payout cycle increased the total number of streaming sessions by 30.7% (=$100\times(e^{0.268}-1)$) for streamers in the treatment group. Second, the positive coefficient estimates columns (3) and (4) suggest that a shorter payout cycle led streamers in the treatment group to add 94.100 more minutes to the total streaming time in a 10-day period, an 80.9% (=$100\times(e^{0.593}-1)$) increase. Finally, the positive and significant coefficient estimates ($p<0.001$) generated in columns (5) and (6) show that in the treatment group, the average streaming sessions were 3.187 minutes longer, or an increase of 40.9% (=$100\times(e^{0.343}-1)$).

	(1) $Session$	(2) $log(Session{+}1)$	(3) $Length$	(4) $log(Length{+}1)$	(5) $Length_a$	(6) $log(Length_a{+}1)$
$Treat \times Time$	2.508***	0.268***	94.100***	0.593***	3.187***	0.343***
	(0.441)	(0.041)	(17.500)	(0.088)	(0.656)	(0.050)
Individual FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Streamers	2424	2424	2424	2424	2424	2424

Observations	43632	43632	43632	43632	43632	43632
R-square	0.410	0.411	0.359	0.383	0.283	0.341

Note. Clustered standard errors at individual streamer level are reported in parentheses. $Session$ = the total number of streaming sessions during each 10-day analysis interval. $Length$ = the total duration of streaming sessions during each 10-day analysis interval. $Length_a$ = the average streaming duration per session during each 10-day analysis interval.

$^{*}p$ < 05. $^{**}p$ < .01. $^{***}p$ <.001

Table 3. Impact of a Shorter Payout Cycle on Streamers' Effort Commitment

Taken together, these results demonstrate that a shorter payout cycle significantly motivated streamers to expend more effort on streaming on the focal gig platforms, thus lending support to Hypothesis 1.

Impact of Payout Cycle on Streaming Quality

To examine the effect on the quality of streaming sessions, we estimate Euqation1 with a set of dependent variables measuring streamers' engagement with listeners. Higher-quality content attracts more listeners and increases the value of gifts given by listeners to streamers. Thus, we compute the total number of listeners and the total gift value received by each streamer in the time interval to proxy the quality of the content produced by the streamer.

We report results in Table4. In columns (1) and (2), the positive and significant coefficients of the interaction term of interest suggest that streamers facing a shorter payout cycle attracted 7.3 more listeners during a 10-day window, which represents a 34.2% increase in the audience size (=100×($e^{0.294}$ −1)). Moreover, the positive coefficients in columns (3) and (4) show that the total value of the gifts given by listeners to streamers in the treatment group was USD 21.723 higher (=21722.900/1000) than that in the control group, which represents a 220.6% increase (=100×($e^{1.165}$ −1)). These results produce strong evidence that when the payout cycle is shorter, the quality of streaming sessions increases, thus corroborating Hypothesis 2.

	(1) $AudienceSize$	(2) $log(AudienceSize + 1)$	(3) $GiftValue$	(4) $log(GiftValue + 1)$
$Treat \times Time$	7.330***	0.294***	21722.900***	1.165***
	(1.946)	(0.052)	(5664.200)	(0.149)
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Streamers	2424	2424	2424	2424
Observations	43632	43632	43632	43632
R-square	0.420	0.429	0.316	0.420

Note. Clustered standard errors at individual streamer level are reported in parentheses. $AudienceSize$ = the total number of listeners who entered the room during each 10-day analysis interval. $GiftValue$ = the total value of gifts the gig worker received during each 10-day analysis interval.

$^{*}p$ < 05. $^{**}p$ < .01. $^{***}p$ <.001

Table 4. Impact of a Shorter Payout Cycle on Streamers' Streaming Quality

There may be concerns that the identified positive impact of a shorter payout cycle on the increased audience size and total gift value may be produced by streamers' expanded efforts in producing more streaming sessions—thus an increase in extensive margin, but not necessarily by the quality of the streaming content. To alleviate this concern, we construct additional measurements as alternative dependent variables—at the finer-grained level of streaming sessions: (a) the average number of listeners per streaming session; (b) the average value of gifts received per streaming session; (c) the average number of listeners who sent gifts per streaming session; and (d) the average time spent watching per streaming session per listener. We aggregate these measures with the average value for each streamer during a 10-day time window.

Table5 reports the results of regressing the first two dependent variables at the session level. We find that the coefficients of the interaction term are consistently positive (p<0.001) in all columns, suggesting that a shorter payout cycle indeed increased the quality of streaming content to attract more listeners and engage listeners to a greater extent. Specifically, column (1) shows that streamers in the treatment group, on average, attracted 0.204 more listeners per session than those in the control group, and column (2) further suggests that the audience size at the individual session level increases by 10.3% (=100×($e^{0.098}$ −1)) for streamers in the treatment group. Furthermore, columns (3) and (4) show that streamers in the treatment group on average received USD 1.867 (=1867.4/1000) more in the total gift value per session than those in the control group, which amounts to a 150.4% (=100×($e^{0.918}$−1)) increase.

	(1) $AudienceSize_a$	(2) $log(AudienceSize_a + 1)$	(3) $GiftValue_a$	(4) $log(GiftValue_a+1)$
$Treat \times Time$	0.204 ***	0.098***	1867.400***	0.918***
	(0.069)	(0.019)	(731.400)	(0.113)
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Streamers	2424	2424	2424	2424
Observations	43632	43632	43632	43632
R-square	0.290	0.339	0.184	0.396

Note. Clustered standard errors at individual streamer level are reported in parentheses. $AudienceSize_a$= the average number of listeners who entered the room per streaming session during each 10-day analysis interval. $GiftValue_a$ = the average total gift value received per streaming session during each 10-day analysis interval.

*p < 05. **p < .01. ***p <.001

Table 5. Impact of a Shorter Payout Cycle on Streamers' Performance: Evidence at the Session Level

Table6 reports the results of the latter two alternative dependent variables of audience engagement at the session level. The positive coefficients (p <0.001) in columns (1) and (2) indicate that in an average session produced by streamers in the treatment group, 0.152 more listeners sent a virtual gift, which was 7.9% (=100×($e^{0.076}$ −1)) higher than the counterpart in the control group. Additionally, the positive coefficients (p<0.001) in columns (3) and (4) demonstrate that, on average, during streaming sessions produced by streamers in the treatment group, listeners stayed 0.993 minutes longer in the virtual room than listeners of sessions produced by streams in the control group, suggesting a 20.6% (=100×($e^{0.187}$−1)) increase.

	(1) $GiftAudience_a$	(2) $log(GiftAudience_a + 1)$	(3) $WatchingLength_a$	(4) $log(WatchingLength_a + 1)$
$Treat \times Time$	0.152 ***	0.076***	0.993***	0.187***
	(0.052)	(0.016)	(0.211)	(0.028)
Individual FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Streamers	2424	2424	2424	2424
Observations	43632	43632	43632	43632
R-square	0.231	0.319	0.110	0.205

Note. Clustered standard errors at individual streamer level are reported in parentheses. $GiftAudience_a$= the average number of audience members who send gifts per streaming session during each 10-day analysis interval. $WatchingLength_a$ = the average watching duration per audience per streaming session during each 10-day analysis interval.

*p < 05. **p < .01. ***p <.001

Table 6. Impact of a Shorter Payout Cycle on Audience Engagement at the Session Level

Taken together, the above analyses provide robust evidence that a shorter payout cycle increases both the efforts expended by streamers and the quality of streaming contents.

Heterogeneous Effects

We examine how the impact of a shorter payout cycle on streamers' outcomes varies for different types of streamers. We focus on streamers with different capabilities of attaining the performance incentive on the focal platform and different levels of commitment prior to the shock. In order to understand these heterogeneous effects, we estimate a difference-in-difference-in-differences (DDD) regression with the model specifications in Equation2:

$$\begin{aligned} \boldsymbol{Y_{it}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 Post_t} \times \boldsymbol{Treat_i} + \boldsymbol{\beta_2 Post_t} \times \boldsymbol{Moderator_i} \\ + \boldsymbol{\beta_3 Post_t} \times \boldsymbol{Treat_i} \times \boldsymbol{Moderator_i} + \boldsymbol{\theta_t} + \boldsymbol{\lambda_i} + \boldsymbol{\epsilon_{it}} \end{aligned} \quad \textbf{(Equation 2)}$$

where $Moderator_i$represents a set of binary variables indicating whether streamer i has a higher capability to attain the performance incentive or whether he/she has a higher level of streaming commitment prior to the shock. Noted that using the binary value as moderators is a common empirical approach in business management literature (Lu et al. 2021; Rishika et al. 2013).[10] All other variables remain the same, as noted in Equation1, and our focal estimation interest is β_3.

We first explore the moderating effect of streamers' tenure on the platform, and we replace $Moderator_i$ in Equation2 with $HighGiftValue_i$, which equals 1 if the total gift value streamer \$i\$ received per time interval on the platform is higher than the median value in the sample and equals 0 otherwise. The results are presented in Table7. We find that the coefficients of the three-way interaction term are consistently positive and statistically significant (p<0.001) across all columns. These results indicate that the positive effects of a shorter payout cycle are more prominent in motivating streamers with higher capabilities to attain the performance incentive to both increase their streaming efforts (Columns 1-3) and enhance the quality of their streaming (measured by the increased audience engagement in Columns 4-5).

10 We also measure streamers' commitment using streaming quality variables such as audience size and gift value received per session, and our analyses demonstrate similar findings. Results are available upon request.

	(1) $log(Session + 1)$	(2) $log(Length + 1)$	(3) $log(Length_a +1)$	(4) $log(AudienceSize_a +1)$	(5) $log(GiftValue_a +1)$
$Post \times Time \times HighGiftValue$	0.366***	0.786***	0.431***	0.153***	0.675***
	(0.077)	(0.168)	(0.094)	(0.009)	(0.025)
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Streamers	2424	2424	2424	2424	2424
Observations	43632	43632	43632	43632	43632
R-square	0.413	0.385	0.342	0.340	0.406

Note. Clustered standard errors at individual streamer level are reported in parentheses. $Session$ = the total number of streaming sessions during each 10-day analysis interval. $Length$ = the total duration of streaming sessions during each 10-day analysis interval. $Length_a$ = the average streaming duration per session during each 10-day analysis interval. $AudienceSize_a$ = the average number of listeners who entered the room per streaming session during each 10-day analysis interval. $GiftValue_a$ = the average total gift value received per streaming session during each 10-day analysis interval. $HighGiftValue$ = 1 if if the total gift value streamer i received is higher than the median value of our analysis sample during the pre-treatment period..
*p < 05. **p < .01. ***p <.001

Table 7. Moderating Effects of Streamers' Capability on the Streamers' Effort Commitment and Streaming Quality

We also investigate the moderating effect of streamers' effort committed on the platform prior to the shock, measured by their total number of streaming sessions and total streaming duration in the pre-treatment period. We replace $Moderator_i$ in Equation2 with $MoreSession_i$ and $LongerDuration_i$, respectively, to estimate the moderating effect. Specifically, $MoreSession_i$ is a binary indicator that equals 1 if streamer i's total streaming sessions are higher than the median value of the sample and equals 0 otherwise. Similarly, $LongerDuration_i$ is a binary variable that equals 1 if streamer i's total streaming length is longer than the median value of the sample and equals 0 otherwise. Table9 summarizes our analysis results. The coefficients of the three-way interaction are consistently positive and significant (p<0.001) across all columns in Section A and Section B, showing that the positive effects of a shorter payout cycle are even stronger for streamers who have previously committed a greater amount of effort commitment on the platform. To test the robustness of the moderating effects, we also apply the continuous value of all moderator measurements to conduct the analyses and observe consistent results (results are avaliable upon request).

Section A	(1) $log(Session +1)$	(2) $log(Length +1)$	(3) $log(Length_a +1)$	(4) $log(AudienceSize_a + 1)$	(5) $log(GiftValue_a+1)$
$Post \times Time \times MoreSession$	0.391***	0.815***	0.428***	0.134***	0.436***
	(0.082)	(0.179)	(0.102)	(0.040)	(0.121)
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Streamers	2424	2424	2424	2424	2424
Observations	43632	43632	43632	43632	43632
R-square	0.414	0.386	0.343	0.340	0.406

Section B	(1) $log(Session+1)$	(2) $log(Length+1)$	(3) $log(Length_a+1)$	(4) $log(AudienceSize_a+1)$	(5) $log(GiftValue_a+1)$
$Post \times Time \times LongerDuration$	0.385***	0.820***	0.438***	0.137***	0.446***
	(0.080)	(0.174)	(0.099)	(0.038)	(0.118)
Individual FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Streamers	2424	2424	2424	2424	2424
Observations	43632	43632	43632	43632	43632
R-square	0.414	0.386	0.343	0.340	0.406

Note. Clustered standard errors at individual streamer level are reported in parentheses. $Session$ = the total number of streaming sessions during each 10-day analysis interval. $Length$ = the total duration of streaming sessions during each 10-day analysis interval. $Length_a$ = the average streaming duration per session during each 10-day analysis interval. $AudienceSize_a$ = the average number of audience members who entered the room per streaming session during each 10-day analysis interval. $GiftValue_a$ = the average total gift value received per streaming session during each 10-day analysis interval. $HighSession$ = 1 if streamer i's total streaming sessions value is greater than the median value of our analysis sample during the pre-treatment period. $HighLength$ = 1 if streamer i's total streaming duration is greater than the median value of our analysis sample during the pre-treatment period.
*p < 05. **p < .01. ***p <.001

Table 8. Moderating Effects of Streamers' Effort Commitment on the Streamers' Effort Commitment and Streaming Quality

Parallel Trend Assumption

To examine the validity of our DID model for causal identification, we first demonstrate evidence on the parallel trend assumption, that is, streamers in the treatment group and control group expended similar efforts in streaming activities before the change to the payout cycle. We use a lead-and-lag model with time interval dummies specified in Equation3.

$$\boldsymbol{Y_{it}} = \boldsymbol{v_0} + \boldsymbol{v_1 TimeDummy_t} \times \boldsymbol{Treat_i} + \boldsymbol{\sigma_t} + \boldsymbol{\eta_i} + \boldsymbol{\xi_{it}} \quad (\boldsymbol{Equation\ 3})$$

where $\boldsymbol{Y_{it}}$ refers to each of the four dependent variables adopted to examine the parallel trend, and $\boldsymbol{TimeDummy_t}$ refers to the set of 10-day interval dummies with the first interval in our observation as the baseline. $\boldsymbol{v_1}$ is a vector of coefficients measuring the dynamic DID estimates. If the parallel trend assumption holds, we expect $\boldsymbol{v_1}$ not to statistically significantly differ from 0 before the shock to the payout cycle. Figure2 demonstrates the estimates of $\boldsymbol{v_1}$ with 95% confidence intervals for each of the dependent variables including total streaming sessions, streaming duration, audience size, and total gift value, and corroborates the parallel trend assumption.

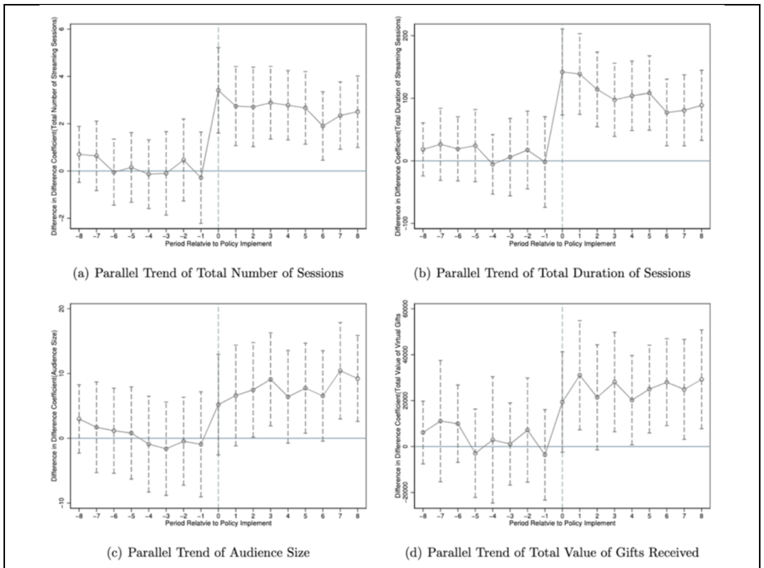

Figure 2. Parallel Trend of Total Number of Sessions

Robustness Checks

We conduct a battery of robustness checks to ensure both the internal and external validity of the identified results. In particular, we verify the parallel trend assumption and conduct falsification tests with both a placebo treatment assignment and a placebo treatment date. We also rule out alternative explanations about the local economy condition, labor market fluctuation, and Covid-19 cases impact by including additional control variables. The results is showed in Table9. Furthermore, we test our results using different model specifications, different samples from India and Pakistan, and apply a different matching procedure with 1:1 and 1:5 nearestneighbor. Our results demonstrate consistent robustness.

	(2) $log(Session + 1)$	(4) $log(Length + 1)$	(6) $log(Length_a + 1)$
$Post \times Treat$	0.312***	0.759***	0.494***
	(0.114)	(0.248)	(0.149)
New Streamers	Yes	Yes	Yes
Inactive Streamers	Yes	Yes	Yes
Unemploymen Rate	Yes	Yes	Yes
Inflation (CPI)	Yes	Yes	Yes
COVID-19 Cases	Yes	Yes	Yes
Downloads	Yes	Yes	Yes
Individual FE	YES	YES	YES
Time FE	YES	YES	YES
Streamers	2424	2424	2424
Observations	43632	43632	43632
R-square	0.411	0.383	0.341

Note. Clustered standard errors at individual streamer level are reported in parentheses. $Session$ = the total number of streaming sessions during each 10-day analysis interval. $Length$ = the total duration of streaming sessions during each 10-day analysis interval. $Length_a$ = the average streaming duration per session during each 10-day analysis interval.

*p < 05. **p < .01. ***p <.001

Table 9. Impact on the Streamers' Effort Commitment with Additional Control Variables

Discussion and Conclusions

Gig platforms have emerged as a prominent method of organizing work in the economy, and a key factor in their success is the use of appropriate governance design to enhance the commitment of gig workers, thereby strengthening the network effect. In this study, we investigate the impact of payout cycle frequency on gig workers' efforts and performance. We propose a theoretical framework based on expectancy theory to generate theoretical predictions. To establish causal identification, we examine a financial settlement system revamp on a mobile voice streaming platform, which served as an exogenous event that shortened the payout cycles for streamers. We employ various methodologies, including matching and the Difference-in-Differences (DID) framework with two-way fixed effects, to allow for plausible causal inference in our analysis.

Contributions

Designing appropriate incentive schemes to increase complementors' participation on a platform is critical for strengthening the indirect network effect, which is vital for the survival and success of the platform (Chen et al. 2022). Among the complementors, gig workers play a particularly important role in gig platforms, which have become increasingly popular as a way of organizing work (Burbano and Chiles 2022; Cameron 2022). While previous research on platform designs has examined the amount and structure of rewards for complementors (Miric et al. 2019; Sun and Zhu 2013), limited attention has been given to other fundamental design elements used by traditional organizations, such as the frequency of these rewards. To the best of our knowledge, our study provides the first empirical evidence demonstrating that the payout cycle is an effective tool to impact both the quantity and quality of work delivered by gig workers on a platform. Additionally, we find evidence that the payout cycle of gig workers also influences customer engagement. These effects lead to a virtuous cycle that contributes to cross-side network effects.

This study also provides a different perspective that deviates from the typical focus of existing research on platform governance, which primarily centers on how platforms can utilize various mechanisms to enhance interactions between workers and customers, and stimulate economic activities among them (Koo and Eesley 2021; Rietveld et al. 2019). Instead, our study demonstrates that effectively managing relationships with gig workers, who act as suppliers of services on the platform, can have a substantial impact on engagement from both the workers' and customers' perspectives. Therefore, it highlights the importance of human capital management as a critical consideration in the design of platform governance strategies.

Furthermore, previous research on human capital management in the context of gig platforms has primarily focused on addressing the challenges of cultivating a sense of meaning and strengthening work identity among workers, given the absence of traditional human capital tools (Ashford et al. 2018; Cameron 2022; Gallus et al. 2023; Petriglieri et al. 2018). The unique nature of flexible labor contracts in the gig economy necessitates the exploration of those non-pecuniary mechanisms. Our study contributes by demonstrating that the payout cycle, a tool that manages pecuniary incentives for gig workers, can also enhance their perception of work and rewards. Consequently, this increases their willingness to work more and be more productive. Thus, we enrich the human capital toolbox by highlighting the importance of payout cycles in this regard.

Limitations and Future Research

This study has several limitations that could serve as opportunities for future research. First, our quasinatural experiment context does not allow us to manipulate the payout frequency at different levels. Thus, we could only examine the effect of the revamped cycle from a 30-day to a 10-day period. Future studies could explore different payout cycles to derive the optimal payout frequency that would help motivate gig workers. Second, we are unable to investigate the interaction effect between the structure of payment (common forms include fixed salary, bonuses, incentives, or pay per performance) and the frequency of the payout cycle. Future studies could explore the moderating effect of payment structure on the payout cycle design. Third, the streaming content was unavailable to us, thus, we are unable to name the specific aspects of streaming content that was improved by gig workers to achieve a better audience experience.

References

Ai, W., Chen, Y., Mei, Q., Ye, J., and Zhang, L. 2023. "Putting Teams into the Gig Economy: A Field Experiment at a Ride-Sharing Platform," *Management Science*.

Akhtar, A. 2019. "More Uber and Lyft Drivers Are Using the App to Fit Their Schedules, but Those Who Make It a Full-Time Job Are Barely Earning a Livable Wage," *Business Insider*.

Anderson, M., McClain, C., Faverio, M., and Gelles-Watnick, R. 2021. "The State of Gig Work in 2021,".

Ashford, S. J., Caza, B. B., and Reid, E. M. 2018. "From Surviving to Thriving in the Gig Economy: A Research Agenda for Individuals in the New World of Work," *Research in Organizational Behavior* (38), pp. 23-41.

Baugh, B., and Correia, F. 2022. "Does Paycheck Frequency Matter? Evidence from Micro Data," *Journal of Financial Economics* (143:3), pp. 1026-1042.

Benson, A., Sojourner, A., and Umyarov, A. 2020. "Can Reputation Discipline the Gig Economy? Experimental Evidence from an Online Labor Market," *Management Science* (66:5), pp. 1802-1825.

Benson, A. M., and Sajjadiani, S. 2018. "Are Bonus Pools Driven by Their Incentive Effects? Evidence from Fluctuations in Gainsharing Incentives," *ILR Review* (71:3), pp. 567-599.

Bhuiyan, J. 2016. "Uber Launches Instant Pay Pilot as It Battles Lyft for Drivers," *Vox*).

Bulletin, C. L. 2022. "China's Livestream Hosts Are Vulnerable to Labour Rights Violations as Workers in the Gig Economy," *China Labour Bulletin*.

Burbano, V. C., and Chiles, B. 2022. "Mitigating Gig and Remote Worker Misconduct: Evidence from a Real Effort Experiment," *Organization Science* (33:4), pp. 1273-1299.

Burtch, G., Carnahan, S., and Greenwood, B. N. 2018. "Can You Gig It? An Empirical Examination of the Gig Economy and Entrepreneurial Activity," *Management Science* (64:12), pp. 5497-5520.

Burtch, G., He, Q., Hong, Y., and Lee, D. 2022. "How Do Peer Awards Motivate Creative Content? Experimental Evidence from Reddit," *Management Science* (68:5), pp. 3488-3506.

Cameron, L. D. 2022. ""Making out" While Driving: Relational and Efficiency Games in the Gig Economy," *Organization Science* (33:1), pp. 231-252.

Campbell, J. P., and Pritchard, R. D. 1976. "Motivation Theory in Industrial and Organizational Psychology," *Handbook of industrial and organizational psychology* (1:63), p. V130.

Cao, X., Zhang, D., and Huang, L. 2022. "The Impact of the Covid-19 Pandemic on the Behavior of Online Gig Workers," *Manufacturing & Service Operations Management* (24:5), pp. 2611-2628.

Carnahan, S., Burtch, G., and Greenwood, B. N. 2017. "Economic and Business Dimensions Unknowns of the Gig-Economy." ASSOC COMPUTING MACHINERY 2 PENN PLAZA, STE 701, NEW YORK, NY 10121-0701 USA, pp. 27-29.

Chen, L., Tong, T. W., Tang, S., and Han, N. 2022. "Governance and Design of Digital Platforms: A Review and Future Research Directions on a Meta-Organization," *Journal of Management* (48:1), pp. 147-184.

Chiang, C.-F., and Jang, S. 2008. "An Expectancy Theory Model for Hotel Employee Motivation," *International Journal of Hospitality Management* (27:2), pp. 313-322.

Conroy, S. A., Roumpi, D., Delery, J. E., and Gupta, N. 2022. "Pay Volatility and Employee Turnover in the Trucking Industry," *Journal of Management* (48:3), pp. 605-629.

De La Rosa, W., Tully, S. M., Jeffrey Inman, J., and Thomas, M. 2022. "The Impact of Payment Frequency on Consumer Spending and Subjective Wealth Perceptions," *Journal of Consumer Research* (48:6), pp. 991-1009.

Etherington, D. 2017. "Uber's Instant Pay Has Cashed out $1.3b to Drivers in Just One Year," *TechCrunch*.

Farrell, D., and Greig, F. 2016. "Paychecks, Paydays, and the Online Platform Economy," *Proceedings. Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association*: JSTOR, pp. 1-40.

Flammer, C., and Kacperczyk, A. 2016. "The Impact of Stakeholder Orientation on Innovation: Evidence from a Natural Experiment," *Management Science* (62:7), pp. 1982-2001.

Friedman, B. A., Cox, P. L., and Maher, L. E. 2008. "An Expectancy Theory Motivation Approach to Peer Assessment," *Journal of Management Education* (32:5), pp. 580-612.
Gallus, J., Campbell, S., and Gneezy, U. 2023. "Awards: Tangibility, Self-Signaling and Signaling to Others," *Self-Signaling and Signaling to Others*.
Gatewood, E. J., Shaver, K. G., Powers, J. B., and Gartner, W. B. 2002. "Entrepreneurial Expectancy, Task Effort, and Performance," *Entrepreneurship theory and practice* (27:2), pp. 187-206.
Gerhart, B., Rynes, S. L., and Rynes, S. 2003. *Compensation: Theory, Evidence, and Strategic Implications*. Sage.
Greenwood, B., Burtch, G., and Carnahan, S. 2017. "Unknowns of the Gig-Economy," *Communications of the ACM* (60:7), pp. 27-29.
Jabagi, N., Croteau, A.-M., Audebrand, L. K., and Marsan, J. 2019. "Gig-Workers' Motivation: Thinking Beyond Carrots and Sticks," *Journal of Managerial Psychology* (34:4), pp. 192-213.
Johnston, H., and Land-Kazlauskas, C. 2018. "Organizing on-Demand: Representation, Voice, and Collective Bargaining in the Gig Economy,".
Kaur, S., Mullainathan, S., Oh, S., and Schilbach, F. 2021. "Do Financial Concerns Make Workers Less Productive?," National Bureau of Economic Research.
Koo, W. W., and Eesley, C. E. 2021. "Platform Governance and the Rural–Urban Divide: Sellers' Responses to Design Change," *Strategic Management Journal* (42:5), pp. 941-967.
Lu, S., Rajavi, K., and Dinner, I. 2021. "The Effect of over-the-Top Media Services on Piracy Search: Evidence from a Natural Experiment," *Marketing Science* (40:3), pp. 548-568.
MacLeod, W. B., and Malcomson, J. M. 1998. "Motivation and Markets," *American Economic Review*), pp. 388-411.
Magloff, L. 2022. "A Fintech Startup Reduces the Turnover of Gig Workers," *Springwise*).
Mehta, I. 2022. "Airbnb Rolls out a Host of New Perks for Hosts," *TechCrunch*.
Mint. 2022. "Platforms Should Assure Gig Workers a New Deal," *Livemint*).
Miric, M., Boudreau, K. J., and Jeppesen, L. B. 2019. "Protecting Their Digital Assets: The Use of Formal & Informal Appropriability Strategies by App Developers," *Research Policy* (48:8), p. 103738.
Nyberg, A. J., Pieper, J. R., and Trevor, C. O. 2016. "Pay-for-Performance's Effect on Future Employee Performance: Integrating Psychological and Economic Principles toward a Contingency Perspective," *Journal of Management* (42:7), pp. 1753-1783.
Oliver, R. L. 1974. "Expectancy Theory Predictions of Salesmen's Performance," *Journal of marketing research* (11:3), pp. 243-253.
Petriglieri, G., Ashford, S. J., and Wrzesniewski, A. 2018. "Agony and Ecstasy in the Gig Economy: Cultivating Holding Environments for Precarious and Personalized Work Identities," *Administrative Science Quarterly* (64:1), pp. 124-170.
Qian, C., Lu, L. Y., and Yu, Y. 2019. "Financial Analyst Coverage and Corporate Social Performance: Evidence from Natural Experiments," *Strategic Management Journal* (40:13), pp. 2271-2286.
Qu, C. B. a. T. 2021. "Millions Turn to Live Streaming to Earn a Living During Covid-19 Pandemic, as the Gig Economy Takes Hold." from https://www.scmp.com/business/companies/article/3138685/millions-turn-livestreaming-earn-living-during-covid-19-pandemic
Rahman, H. A., and Valentine, M. A. 2021. "How Managers Maintain Control through Collaborative Repair: Evidence from Platform-Mediated "Gigs"," *Organization Science* (32:5), pp. 1300-1326.
Reinicke, C. 2022. "44% of Americans Work a Side Hustle to Make Ends Meet — but It May Not Be an Efficient Way to Earn More, Says Expert." from https://www.cnbc.com/2022/06/27/44percent-of-americans-work-a-side-hustle-to-make-ends-meet.html#:~:text=Grow.-,44%25%20of%20Americans%20work%20a%20side%20hustle%20to%20make%20ends,to%20earn%20more%2C%20says%20expert&text=Americans%20are%20increasingly%20turning%20to,uncertainty%20and%20persistent%20high%20inflation.
Renko, M., Kroeck, K. G., and Bullough, A. 2012. "Expectancy Theory and Nascent Entrepreneurship," *Small Business Economics* (39), pp. 667-684.
Rietveld, J., Schilling, M. A., and Bellavitis, C. 2019. "Platform Strategy: Managing Ecosystem Value through Selective Promotion of Complements," *Organization Science* (30:6), pp. 1232-1251.
Rishika, R., Kumar, A., Janakiraman, R., and Bezawada, R. 2013. "The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation," *Information systems research* (24:1), pp. 108-127.

Schunk, D. H. 1991. "Self-Efficacy and Academic Motivation," *Educational psychologist* (26:3-4), pp. 207-231.

Singh, J., and Agrawal, A. 2011. "Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires," *Management Science* (57:1), pp. 129-150.

Smith, R. A. 2022. "More Workers Get Side Hustles to Keep up with Rising Costs." from https://www.wsj.com/articles/more-professionals-need-to-get-second-jobs-because-of-inflation-11667774723

Sun, M., and Zhu, F. 2013. "Ad Revenue and Content Commercialization: Evidence from Blogs," *Management Science* (59:10), pp. 2314-2331.

Vallas, S., and Schor, J. B. 2020. "What Do Platforms Do? Understanding the Gig Economy," *Annual Review of Sociology* (46:1), pp. 273-294.

Vroom, V. H. 1964. "Work and Motivation,").

Wong, S. I. 2022. "Job Crafting Can Help Digital Gig Workers Build Resilience," *Harvard Business Review*).

Wong, S. I., Kost, D., and Fieseler, C. 2021. "From Crafting What You Do to Building Resilience for Career Commitment in the Gig Economy," *Human Resource Management Journal* (31:4), pp. 918-935.

Wood, A. J., Graham, M., Lehdonvirta, V., and Hjorth, I. 2019. "Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy," *Work, employment and society* (33:1), pp. 56-75.

Woodcock, J., and Graham, M. 2019. "The Gig Economy," *A critical introduction. Cambridge: Polity*).

Wu, Q., Zhang, H., Li, Z., and Liu, K. 2019. "Labor Control in the Gig Economy: Evidence from Uber in China," *Journal of Industrial Relations* (61:4), pp. 574-596.

Younge, K. A., Tong, T. W., and Fleming, L. 2015. "How Anticipated Employee Mobility Affects Acquisition Likelihood: Evidence from a Natural Experiment," *Strategic Management Journal* (36:5), pp. 686-708.

Zeng, Z., Clyde, N., Dai, H., Zhang, D., Xu, Z., and Shen, Z.-J. M. 2020. "The Value of Customer-Related Information on Service Platforms: Evidence from a Large Field Experiment," *Available at SSRN 3528619*.