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

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Completed Research Paper

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Abstract

Despite their astounding growth in recent years, online gig platforms face key challenges to increase gig workers' working commitment. In this study, we investigate how a higher payout frequency may stimulate workers' commitment to work, improve the work quality, and engender heterogeneous impacts across different workers. Drawing on the expectancy theory and using detailed data from a multinational streaming platform, we explore a quasi-natural experiment. Leveraging an exogenous shock of a financial system upgrade, we employ the propensity score matching (PSM) technique with a difference-in-differences (DID) approach to demonstrate that a shorter payout cycle increased gig workers' efforts at work. Moreover, a shorter payout cycle increased the quality of work. The positive impact was more pronounced for workers with a shorter tenure and for those who had a higher commitment to work before the treatment. Our results help gig platforms understand how to design payout schemes to motivate gig workers.

Keywords: Gig Economy, Payout Scheme, Worker Commitment, Incentive and Motivation, Quasi-natural Experiment

Introduction

The "gig economy," defined as online labor markets for independent and flexible contracting (Burtch et al. 2018; Woodcock and Graham 2019), has been growing exponentially in recent years around the globe (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 motivating gig workers to deliver high-quality work (Wong 2022). Indeed, constrained by the flexible

[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-global-gigeconomy-2020.pdf

labor contracts with gig workers, gig platforms 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 (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). Thus, lacking abilities to tackle these challenges could substantially undermine a platform's profitability and long-term growth. (Burbano and Chiles 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 from 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 (Etherington 2017). Similarly, 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).

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 (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 (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 and Tully 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. Indeed, a primary reason people engage in gig work is to earn supplemental income to meet the financial needs that their primary incomes cannot satisfy (Monica et al. 2021). For instance, 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). 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. 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; Renko et al. 2012).

To empirically examine our hypotheses, we collaborated with a 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 listeners in their chat rooms. Streamers provide services including streaming content and interacting with listeners, and they receive payment in the form of virtual gifts from listeners in each streaming session. Thus, a primary reason for streamers to join the platform is to earn supplemental income in order to cover daily expenses. The platform works with local finance settlement vendors in local regions to collect online payments from listeners 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 (Qian et al. 2019), 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' tenure of operation and 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.[3] 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) but need to ascertain whether such practices can indeed achieve the intended goals. Notably, because attaining new workers and retaining committed workers are essential for the sustainable growth of gig platforms, the findings that the effect was more pronounced for workers who were newer or were making higher commitments to the platform are especially encouraging.

Related Literature

Payout Scheme and Employee Performance

Motivating employees to sustain their commitment to work and to ensure consistent delivery of quality work is a central task in the management of human resources. A large body of literature has explored how the amount or structure of payout, such as salaries and bonuses, affects workers' productivity by shaping the valence of pay. Research has shown that larger bonus sizes (Bareket-Bojmel et al. 2017) and higher perceived economic value of payment (Kryscynski 2021) improve employee performance and reduce their turnover rate, albeit with some exceptions (Shen and Hirshman 2022). Commonly examined structures of payout include fee-for-service versus lump-sum payments (Adida et al. 2017; Nyberg et al. 2016).

A large body of management literature has examined how pay-for-performance schemes increase employee performance by elevating the level of instrumentality or expectancy, (Bareket-Bojmel et al. 2017; Nyberg et al. 2016; Solbach et al. 2022), reduce the turnover of highperforming employees (Shaw 2015), motivate high-quality providers to improve performance in healthcare (Rosenblat and Stark 2016), and generate positive spillovers on non-incentivized work (Frankort and Avgoustaki 2022) and helping behavior at work (He et al. 2021).

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

Compared with the amount or structure of payouts, the existing literature has offered more limited insights on the frequency of payout, another important component of any payment scheme. Nonetheless, it shows that more frequent payments increase workers' liquidity (Baugh and Correia 2022), thus improving individuals' perception of their own wealth (De La Rosa and Tully 2022), which in turn reduces employees' mental burdens about financial security (Kaur et al. 2021). More frequent payouts also increase the psychological salience of the payment (Frankort and Avgoustaki 2022). These factors enable shorter payout cycles to boost the motivation of employees in traditional organizations.

However, as discussed in Section 1, increased liquidity and perceptions of more wealth and financial security may *undermine* the motivation of most gig workers to generate supplemental income from their work, and the cyclical nature of gig work also reduces its psychological salience. Therefore, the existing theories developed on the implication of payout cycles for employees in traditional organizations appear to predict the opposite effect for gig workers.

Features of Gig Platforms

Like most two-sided markets, gig platforms need to address two critical issues including information asymmetry and user engagement (Duggan et al. 2020). First, customers face a high level of uncertainty when dealing with unbranded service providers with diverse qualities on gig platforms (Ashford et al. 2018; Burtch et al. 2018; Luo et al. 2021). The extant studies explored various platform feature designs to mitigate information asymmetry and boost customers' confidence in the quality of service, such as providing photographic information for customers (Zhang et al. 2022), enabling providers to develop reputations (Benson et al. 2020), and sharing organizational value with gig workers (Burbano and Chiles 2022).

Second, the prior literature also investigated platform features that help attain gig workers (Jabagi et al. 2019). For instance, monetized tipping and gifting for gig workers' performance substantially increase their productivity and work commitment (Wang et al. 2022). Using peer recognition and peer presence could also drive the productivity of gig workers in delivering better-quality work (Gallus 2017; Lu et al. 2021b; Reiff et al. 2022). Platforms could optimize their work assignment algorithm to increase gig workers' flexibility and autonomy over their jobs, which improve their performance (Rosenblat and Stark 2016).

Whereas most research has focused on the impact of explicit user interface design, amount of financial returns, and non-monetary incentives on gig workers' motivations, we examine a seemingly mundane but highly important back-end system design, the payout cycle for gig workers.

Hypothesis Development

Payout schemes can motivate employees to exert more effort at work (Kahneman 1973; Prendergast 1999). A rational view is that employees have forward-looking expectations to compare the benefits of rewards with the cost of their efforts (Prendergast 1999). Thus, designs of payout schemes can shape employee efforts by increasing the net present value of payment (Renko et al. 2012).

However, workers may not always see their payoffs through the lens of rational benefit-cost analysis. A cognitive view emphasizes how workers *perceive* various aspects of payment schemes. For example, due to the finite capacity of workers' attention, a payout that occurs at a more distant time from the delivery of their work would render the reward for their effort less cognitively salient in their perception (Kahneman 1973). Therefore, payment cycles can serve as a periodic stimulus that shapes employees' motivation (Frankort and Avgoustaki 2022).

The expectancy theory is a common theoretical lens to explore how workers perceive their rewards, which in turn shapes workers' motivation (Nyberg et al. 2016). The expectancy theory establishes three main channels that steer individual behaviors: expectancy (the belief that one's efforts could lead to desired goals), instrumentality (the belief that if the performance expectation is met, the reward would follow), and valence (the value of the reward) (Vroom 1964). Prior studies have concluded that organizations could increase employees' work motivation and commitment by designing incentive schemes that increase any of these three components (Renko et al. 2012). Drawing on this literature, research shows that the component of employees' reward expectancy is affected by self-efficacy, goal difficulty, perceived control, and previous incentive experience (Chiang and Jang 2008; Vroom 1964).

Compared to employees in traditional organizations, gig workers generally have lower expectancy because several key features of their work results in a perception of more tenuous connections between efforts and rewards. Gig workers perceive higher uncertainty over whether their efforts could lead to expected rewards for two reasons (Ashford et al. 2018; Wong et al. 2021). First, gig workers tend to have lower self-efficacy to commit to the work because many of them only participate in the platform as a part-time job (De La Rosa and Tully 2022). It may be difficult for them to commit to the time frame of delivery and expected quality. Second, gig workers tend to perceive greater difficulty to achieve goals because of the nature of their work relationship with the platforms. Gig workers need to leverage, to a greater extent, their own capabilities and resources to deliver the promised work without abundant organization resources support (Petriglieri et al. 2019). Thus, looming uncertainty over whether efforts expended could achieve expected rewards undermines gig workers' motivation to devote efforts (Grant 2007).

A shorter payout cycle can reduce this uncertainty by enhancing gig workers' *expectancy* for future rewards. First, a shorter payout cycle enables gig workers to receive more frequent payouts, which enhances the stimuli effect of the receipt of actual incentive payment. More-frequent periodic stimuli of incentive payout enhance the perception that workers' efforts could attain the desired reward (Nyberg et al. 2016), thus higher expectancy. Second, more frequent payouts enable gig workers to recall the moments when customers rewarded them for their work, which reinforces the perception of the positive relationship between efforts and rewards. Thus, gig workers are motivated to expand more efforts in the future after receiving an incentive payment.
Therefore, we construct our first hypothesis as follows:

Hypothesis 1: A shorter payout cycle increases the efforts expended by gig workers on the platform.

A shorter payout cycle also increases gig workers' perceived *instrumentality* that good work will be rewarded. First, payout incentive provides positive feedback on the performance of gig workers (Shaw 2015). A shorter payout cycle more frequently reminds gig workers of the quality of their work that has earned them the payment, thus reaffirming, in their mind, that meeting performance expectations generates reward, thus higher instrumentality (Frankort and Avgoustaki 2022; Petriglieri et al. 2019). Thus, gig workers would pay greater attention to improving their performance quality to increase future payments. Second, a shorter payout cycle will make the variations in payment amounts more cognitively salient. Because the quality provided by gig workers might vary by case, only the work whose quality has met clients' expectations will be rewarded (Ashford et al. 2018). The variations in each payout remind gig workers that only better performances will be rewarded (Ashford et al. 2018). Therefore, gig workers not only need to expend efforts in delivering more work but also need to devote efforts to improving the quality of their work in order to attain the reward. Therefore, we develop the following hypothesis:

Hypothesis2: Ashorterpayoutcycleimprovesthequalityofworkperformedbygigworkers on the platform.

Noted that in the gig economy context, the impact of a shorter payout cycle on valence, the third channel of the expectancy theory, is less salient for two reasons. First, unlike the consistent wages of traditional full-time jobs, gig work payouts are typically proportional to the level of demand and can vary significantly (Ashford et al. 2018). Indeed, the hourly income of most gig jobs varies between $ 7 and $ 15, the demand fluctuates, and the majority of gig workers believe that they could be paid better if they were working in a traditional full-time job (Brower 2022). Second, many gig workers participate in multiple gig jobs on various platforms (Caza et al. 2018). As a result, the change of payout cycle in one gig platform would not substantially reduce the valence in the mind of gig workers. These factors reduce the perceived valence of the amount of each payment for gig workers.

We further explain how the identified effects vary across gig workers with different operation tenure and prior work commitment. According to the expectancy theory, workers' past experience with incentive schemes could substantially shape their expectancy and instrumentality for future reward (Vroom 1964).

Recall that gig workers face high uncertainty of future incentives (Ashford et al. 2018). This is particularly true for gig workers who newly join the platform as they have accumulated less experience with the incentives schemes offered on the given platform in the past and fewer memories of events that demonstrate rewards for quality work (Nyberg et al. 2016). As a result, the perceptions of expectancy or instrumentality that connect their efforts with rewards on the given platform is less established for newer gig workers (Nyberg et al. 2016). When a shorter payout cycle enhances perceived expectancy or instrumentality of future rewards, the magnitude of this increase should be larger for gig workers with shorter tenures on the platform. We thus propose the following hypotheses:

Hypothesis 3: The impact of a shorter payout cycle on the (a) efforts and (b) quality of work is more pronounced for gig workers who are newer to the gig platform.

The effect produced by a shorter payout cycle is also more pronounced for gig workers who exert higher commitment to the platform. More-committed gig workers pay greater efforts in their work on the platform, by either increasing the amount of work done (higher external margin), enhancing the quality of work (higher internal margin), or both. This means that, during an average payout cycle, they are likely to have earned higher rewards from their work (Faisal Ahammad et al. 2015). When a shorter payout cycle results in more frequent occurrences of payment, more-committed workers experience even stronger enhancements of expectancy and instrumentality. We thus propose the following hypotheses:

Hypothesis 4: The impact of a shorter payout cycle on the (a) efforts and (b) quality of work is more pronounced for gig workers who make a greater commitment to their work on the gig platform.

Empirical Setting and Data

The Platform

The platform is a voice streaming app that hosts individual voice streamers to share their personal stories, showcase their talents, and earn virtual gift appreciation from 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. 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. To earn some supplement income from listeners’ virtual gifts, 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. The platform randomly selected chatrooms to display on the landing page). 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 Figure 1 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.

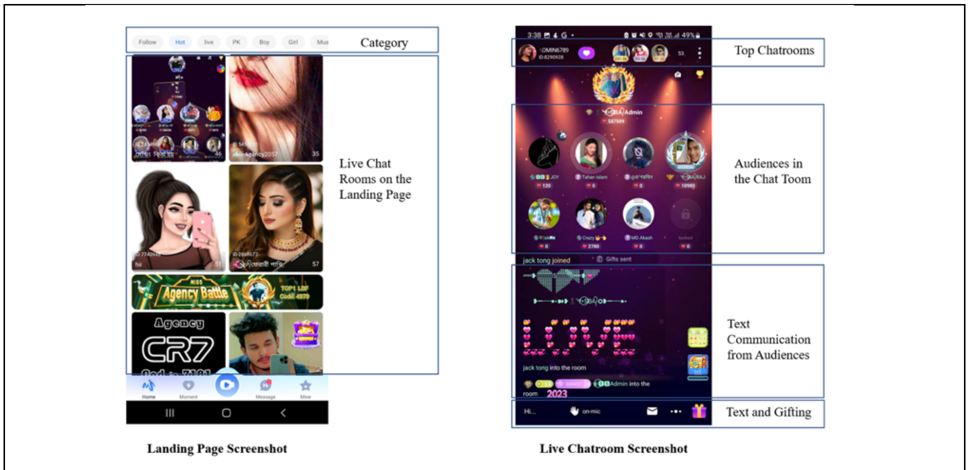

Figure 1. Screenshot of the Landing Page and Live Chat Room

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.[4]

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 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-to-customer 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

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

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.

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.[5] 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.[6] 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.[7] We adopt a 1:3 nearest-neighbor matching method with the replacement for the matching procedure. The matched outcomes are summarized in Table1. 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

[5] 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.

[6] 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/

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

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

Note. N = 2424. Control = 606. Treat = 1818. U = unmatched data. M = matched data.

Table 1. PSM Matching Balance Check

To examine the validity of our DID model for the causal identification, we first demonstrate evidence that supports 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 Equation 1.

$$\boldsymbol{Y_{it} = v_0 + v_1 TimeDummy_t \times Treat_i + \sigma_t + \eta_i + \xi_{it}} \qquad \textbf{(Equation 1)}$$

where Y_{it} refers to each of the four dependent variables adopted to examine the parallel trend, and $TimeDummy_t$ 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. Figure 2 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.

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 Equation 2.

$$\boldsymbol{Y_{it} = \alpha_0 + \alpha_1 Post_t \times Treat_i + \theta_t + \lambda_i + \epsilon_{it}} \qquad \textbf{(Equation 2)}$$

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

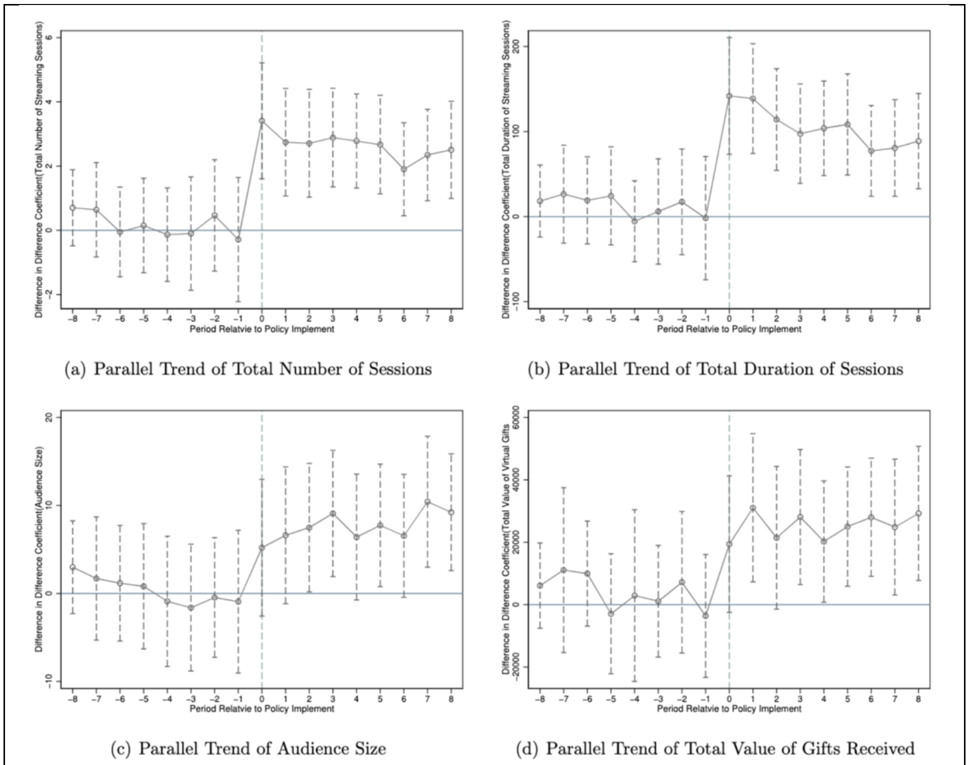

Figure 2. Parallel Trend of Total Number of Sessions

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.

Table2 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×($e^{0.343}$ −1)). 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.

	(1) $Session$	(2) $log(Session + 1)$	(3) $Length$	(4) $log(Length + 1)$	(5) $Length_a$	(6) $log(Length_a + 1)$
$Post \times Treat$	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 2. Impact of a Shorter Payout Cycle on Streamers' Effort Commitment

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 Table3. 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.

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.

	(1)	(2)	(3)	(4)

	$AudienceSize$	$log(AudienceSize + 1)$	$GiftValue$	$log(GiftValue + 1)$
$Post \times Treat$	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 3. Impact of a Shorter Payout Cycle on Streamers' Streaming Quality

Table4 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% (= $100\times(e^{0.098}-1)$) 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% (= $100\times(e^{0.918}-1)$) increase.

	(1) $AudienceSize_a$	(2) $log(AudienceSize_a + 1)$	(3) $GiftValue_a$	(4) $log(GiftValue_a + 1)$
$Post \times Treat$	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 4. Impact of a Shorter Payout Cycle on Streamers' Performance: Evidence at the Session Level

Table5 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% (= $100\times(e^{0.076}-1)$) 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% (= $100\times(e^{0.187}-1)$) increase.

	(1) $GiftAudience_a$	(2) $log(GiftAudience_a + 1)$	(3) $WatchingLength_a$	(4) $log(WatchingLength_a + 1)$
$Post \times Treat$	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 5. 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. To test Hypotheses 3 and 4, we focus on streamers with different operation tenures on the focal platform and different levels of commitment before the shock. In order to understand these heterogeneous effects, we estimate a difference-in-difference-in-differences (DDD) regression with the model specifications in Equation 3:

$$\begin{aligned}\boldsymbol{Commitment_{it}} &= \boldsymbol{\beta_0 + \beta_1 Post_t \times Treat_i + \beta_2 Post_t \times Moderator_i} \\ &\quad \boldsymbol{+\beta_3 Post_t \times Treat_i \times Moderator_i + \theta_t + \lambda_i + \epsilon_{it}}\end{aligned} \qquad \textbf{(Equation 3)}$$

where $Moderator_i$ represents a set of binary variables indicating whether streamer *i* has a lower tenure or a higher streaming commitment on the date of the payout cycle revamp, which is consistent with empirical practices in business literature (Lu et al. 2021a; Rishika et al. 2013). We calculate streamer *i*'s tenure using the number of days since they joined the platform and their effort commitment in terms of the total streaming sessions and total streaming duration in the pre-treatment period. Then, we conduct a median split to determine their tenure and commitment level (e.g., low vs. high).[8] 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 Equation 3 with $ShortTenure_i$, which equals 1 if streamer i's tenure on the platform is shorter than the median value in the sample and equals 0 otherwise. The results are presented in Table8. We find that the coefficients of the three-way interaction term are positive and statistically significant ($p < 0.001$) across all columns, suggesting that the positive impacts of a shorter payout cycle are more pronounced in motivating streamers with a shorter tenure.

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 Equation 3 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.

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 have incorporated a set of time-varying country-level covariates in Equation 2 to address several concerns over endogeneity that were created by unobserved post-treatment confounds, such as fluctuations in local labor markets, unstable economic conditions, the potential impact of COVID-19, platform competition or expansion and platform population, which could affect both motivations of streamers and audience engagement. 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 nearest-neighbor. Our results demonstrate consistent robustness.

Discussion and Conclusions

Driven by the increasing challenges faced by gig platforms to increase gig workers' commitment to work, we investigate the impact of the frequency of the payout cycle on gig workers. Our argument is that the prevailing theories regarding the impact of shorter payout cycles on traditional employees do not sufficiently account for the unique relationship between gig workers and platforms. Therefore, we put forth a theoretical framework based on the expectancy theory to account for the distinctive circumstances that gig workers face, and to produce theoretical predictions. We leverage an exogenous event of a payout cycle revamp on a mobile voice platform as well as a variety of methods including matching and DID framework with two-way fixed effects to produce plausibly causal identification.

Contributions

Most organizations and platforms leverage the composition design of payout schemes (e.g., salary and incentive) to motivate workers' commitment, but they largely ignore the potential impact of payout frequency. Our study, which to the best of our knowledge constitutes the first piece of empirical evidence on the impact of payout cycles on gig workers, shows that a shorter payout cycle significantly increases gig workers' effort exerted at work. In addition to the increased external margin, we also demonstrate that a

[8] 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.

shorter payout cycle increased the internal margin, by enhancing gig workers' quality of work, resulting in greater audience engagement. Improved extensive and intensive margins increase income for workers and revenues for platforms.[9]

The discovery that shorter payout cycles have an even greater impact on gig workers with shorter tenures and those with higher commitment to work offers significant support to gig platforms in tackling the obstacles of high turnover rates and low commitment to work. This is especially true for newer workers who are at greater risk of churn because they are still testing out the platform, and for more committed workers who are valuable for platforms to maintain consistent work quality. The particularly salient effect of shorter payout cycles on those two groups of gig workers is crucial for gig platforms to achieve sustainable business growth. Thus, payout cycle design deserves greater attention as an effective strategy for gig platforms to retain and motivate workers. Further, a more frequent payout scheme needs the support of a more agile finance settlement system. Our study provides a solid theoretical and empirical basis for platforms' investment in upgrading back-end IT infrastructure.

Lastly, our results suggest that a simple payout cycle design could substantially improve the economic status of gig workers in developing countries. In particular, our model estimation on the effect magnitude suggests that the additional efforts expended by gig workers help them attain USD 21.7 dollars more in a 10-day time period, which translates into around USD 65 monthly incremental income or USD 780 annual incremental income. The income lift for these gig workers in Bangladesh is nontrivial because this income lift is equivalent to 1/3 of the GDP per capita (USD 2,500) in the local region, indicating that the additional income earned through gig work could play a vital role in improving the economic status of populations in developing countries like Bangladesh.

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.

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