Wage theft, reneging and liquidity constraints in informal labor markets *

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March 16, 2025

Abstract

Informal labor markets in low- and middle-income countries are characterized by high unemployment and job turnover, despite high labor demand. I conduct three field experiments to examine how frictions arising from wage theft, worker reneging and liquidity constraints lead to a mismatch in workers' labor supply and firms' labor demand in these markets. In the first experiment, 1,360 workers receive real job offers on either flat contracts (paid daily), which reduce wage theft concerns and worker liquidity constraints, or back-loaded contracts (paid at end of contract), which don't. To isolate the effects of wage theft concerns I cross-randomize these contracts with an insurance contract. I find that labor supply is three times larger for flat contracts. This preference is driven by workers' fears of wage theft by firms (28%), liquidity constraints (22%), and demand for flexibility to break contracts (50%). This flexibility captures an option value, protecting workers from income loss in the event of future shocks or excess work exaction by firms under back-loaded contracts. The costs of these frictions are high—72% of workers who reject job offers end up earning less income than those offers would have provided. In the second experiment, I make real offers to hire workers on either flat or back-loaded contracts to 349 firms. The firms' labor demand doubles for back-loaded contracts, driven by liquidity constraints (37%) and costs associated with worker reneging (63%) in flat contracts. In a third experiment, firms and workers who accepted contracts in the first two experiments are matched with each other. Workers are 69% more likely to complete back-loaded contracts compared to flat contracts, which have a completion rate of 34% and thereby impose significant costs on firms. Firms exact longer working hours from workers in back-loaded contracts, validating the workers' concerns. My findings suggest that improving contract enforcement and providing credit to firms can reduce welfare losses in equilibrium and improve efficiency.

*I am grateful to my advisors Michael Kremer, Christina Brown, Anne Karing and James Robinson for valuable comments, support, advice and guidance. I thank Arun Chandrasekhar, Michael Dinerstein, Chinmaya Kumar, Erin Kelley, Sabareesh Ramachandran, and seminar audiences at the University of Chicago and NEUDC for helpful comments. Jay Prasad provided excellent research assistance. I am deeply indebted to the field team in Patna led by Gufran Ahmad and Neeraj Kumar. This work would not have been possible without helpful discussions with Gufran Ahmad, Raman Singh Chhina, Karan Jain, Sabahat Ali Khan, Neeraj Kumar, Randhir Kumar, Avinash Kumar, Rakesh Kumar, Madan Paswan, Jay Prasad and Manoj Yadav. The project was funded by the Development Economics Research Fund at the University of Chicago, the Weiss Fund, and the Pearson Institute. The IRB approval for this project was provided by the University of Chicago. The experiment was registered at AEA RCT registry (AEARCTR-0013100).

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1 Introduction

Informal firms in low- and middle-income countries often hire casual workers on short-term contracts. These firms are typically small, have low cash flow, high costs related to worker search and separation, and often find it difficult to hire workers.[1] Many of these firms recruit from labor stands (Breza et al. (2019), Breza et al. (2021)), where millions of workers seek employment. These workers are extremely poor, often requiring daily remuneration for subsistence, face high search costs, and experience high levels of unemployment.[2] The institutional environment is marked by challenges in enforcing contracts, and both workers and firms renege on contracts.[3]

When workers can renege on contracts, firms may prefer to back-load wages in order to incentivize workers to stay with the firm over time (Thomas and Worrall (1988), Holmstrom (1983)), reducing the costs associated with worker turnover and search (Caria et al. (2024)).[4] However, in the absence of institutions that enforce contracts, workers are concerned about wage theft by firms, and worry that employers may extract excess hours of work without compensation (Praveen (2024)). Back-loading increases the amount withheld by the firm at the end of any day, and thereby the potential loss if the firm reneges on payment.[5] In equilibrium, limited commitment from workers can increase job turnover and firm search costs, while limited commitment from firms may increase wage theft.

Low cash flow constrains the liquidity of informal firms (Sharma et al. (2024)), reinforcing their preference for back-loading contracts.[6] Similarly, low-income workers face consumption credit constraints, and might tend to prefer flat contracts which pay wages daily. These liquidity constraints—on both sides—combined with limited commitment, can lead firms and workers to prefer specific payment structures in contracts. Mismatches in these preferences can result in unemployment, despite demand, ultimately affecting economic efficiency and overall welfare. Limited commitment and liquidity constraints push the preferences of firms and workers in the same direction, but have different policy implications. Therefore, it's crucial to disentangle their effects and determine whether firms' and workers' priors about each other's likelihood of reneging are accurate.

This paper studies the consequences of limited commitment and liquidity constraints on the demand and supply of labor in informal labor markets in India. I develop a theoretical framework and use three field experiments with firms and workers in the construction industry to answer the following questions: i) How do liquidity constraints and concerns about wage theft (limited commitment on the

[1] In my sample, firms' losses amount to approximately 10-20% of a worker's daily wage if the worker fails to show up for a day. 54% firms state that they face delays in hiring a worker.

[2] The workers in the experiment sample spend approximately 8% of their daily wage on search activities and find work on only 2.4 out of every 4 days. During lean periods, unemployment is almost always above 50%.

[3] 79% of firms experienced worker reneging in the two months prior to our survey, and 53% of workers in our sample knew of others who had reneged on contracts. Additionally, 12% of workers faced at least one instance of non-payment in the month before the survey.

[4] Back-loaded contracts are those in which a larger portion of the cumulative payment is distributed over the latter part of the contract. Flat or daily pay contracts are those which pay the workers their due wages at the end of each day.

[5] Reputation-based arrangements can partially alleviate worker-firm mistrust; however, they tend to limit search to existing networks, which can be inefficient (Chandrasekhar et al. (2020)), and have limited impact in informal markets characterized by high churn. In agricultural markets, where the landowners and agricultural laborers frequently interact with each other, the practice of labor-tying can reduce these frictions (Bardhan (1983)).

[6] 30% of the firms in my sample are not paid in time by their own employers.

firm's end) affect the labor supply of workers? ii) How do liquidity constraints and concerns about worker reneging (limited commitment on the workers' end) affect the labor demand of firms? iii) Finally, do firms and workers renege on contracts when institutions enforcing them are absent? The two frictions I highlight can lead to divergence in contractual preferences of workers and firms which could explain the high unemployment and job turnover rates in informal markets of low- and middle-income countries. While I focus on workers at labor stands, the frictions I highlight characterize the informal economy at large, and have been referred to in other settings.[7]

I proceed as follows. First, I use descriptive data to establish key facts about limited commitment and liquidity constraints and the costs they impose on low-income workers seeking employment at labor stands and the informal firms hiring at these sites. I then incorporate these facts into a simple model, where agents differ in liquid assets and both sides have limited commitment. This model outlines the trade-offs firms and workers face in hiring and job acceptance decisions. Finally, I generate predictions about their contract preferences and actions within those contracts as the costs of liquidity constraints and potential reneging by either party change. My model shows that firms prefer back-loaded contracts to reduce worker turnover and search costs when worker commitment is limited (Thomas and Worrall (1988), Holmstrom (1983), Ray (2002), Lazear (1981)), and that liquidity constraints reinforce this preference, as firms must borrow to pay workers beyond their liquid assets.

On the worker side firms might not pay workers with a positive probability at the end of the work day, and the loss from wage theft increases in the intensity of back-loading, pushing workers to prefer contracts which pay their due wages daily.[8] Liquidity constraints reinforce these preferences for workers as they require some wages daily for consumption.[9] Effort is costly for workers, who want to contract on fixed number of hours of work for each day.[10] Firms have an incentive to increase the number of working hours. A back-loaded contract reinforces this incentive as workers face losses on unpaid wages if they renege when asked to work more hours than agreed. This, in turn, strengthens workers' preferences for *flat* or *daily pay* contracts.[11]

Next, I test the model's predictions through an experiment in the construction labor market in Patna, India. This industry contributes around 8% to India's GDP and employs approximately 57.7 million unskilled workers (Baijal and Awasthi (2023)). Small informal firms seeking to hire workers were recruited through snowball sampling. Workers were given real job offers at labor stands for the experiment. In order to isolate the effects of liquidity constraints and limited commitment, I design three contracts with different payment structures. These contracts, developed through surveys of

[7]Farazi (2014) highlights informal firms' liquidity constraints, Breza et al. (2018), Krishnaswamy (2019) explore worker reneging/absenteeism, and Saha et al. (2024) investigates wage theft in the Indian tea industry.

[8]Intensity of back-loading is a measure of the total wages that remain unpaid at the end of a working day in the contract.

[9]Precautionary saving motives could push workers to prefer back-loaded contracts especially when preferences are time inconsistent (Thaler and Benartzi (2004), Ashraf et al. (2024)).However, these forces are less relevant for workers who consume a large portion of their daily income (Carroll et al. (2021)).

[10]In mysetting, it's common knowledge among workers that total working hours for a commonly known daily wage is 8 hours. Negotiations between firms and workers often involve discussion over timings, with 9 am to 5 pm and 9:30 am to 5:30 pm being the most common ones.

[11]Henceforth, we refer to flat contracts as daily pay contracts.

firms and workers, relax one constraint at a time. They represent a subset of the agreements that workers and firms engage in under equilibrium. In *steep back-loaded* contracts, firms pay workers a portion of their wages on the first day and the remainder on their last day of work, reducing the firm's liquidity constraints and risk of reneging by workers. However, this contract imposes liquidity constraints and the greatest risk of wage theft on workers.[12] In *smooth back-loaded* contracts, firms pay workers a fixed portion of their wages daily, with the remaining wages paid at the end of the contract. This contract imposes liquidity constraints on firms but reduces risk of reneging. For workers, this contract increases potential losses from wage theft while reducing their liquidity constraints. Under *daily pay* or flat contracts, firms pay workers their due wages at the end of each day, reducing both liquidity constraints and wage theft concerns for workers while imposing liquidity constraints and costs of reneging on firms.[13] These three contracts are cross-randomized with other treatments, as described below.

In the first experiment, 1360 workers at labor stands or spot markets (who are looking for work) are given job offers to work at construction sites on randomly chosen contracts. The job is the same across all offers. To formally test whether the labor supply is driven by concerns about wage theft, I cross-randomize the three contracts described above with a zero-cost insurance treatment, which is offered to randomly selected workers. The insurance treatment arm guarantees the workers that their due wages will be paid by the field team if the firm reneges.[14] We offer contracts of two lengths, 3 and 7 days, which are cross-randomized with the six contracts, giving a total of 12 treatment cells.

In the second experiment, I offer to hire workers for 349 informal construction firms (who are looking to hire workers) on the three contracts mentioned above: daily pay, smooth back-loading, and steep back-loading. The steep back-loading treatment does not fully alleviate the firm's liquidity constraints, so I offer a *credit* contract to firms to address this issue. The *credit* contract also alleviates the transaction cost of paying workers.[15] Additionally, a *guarantor* contract that provides compensation if the worker breaks the daily pay contract is offered to firms. At the end of the first two experiments, I get a set of firms and workers which have agreed to specific contracts. The worker and firm experiments give me an incentive-compatible measure of worker and firm preferences. Then, I randomly match the firms and workers within each contract.[16] For each worker-firm pair, I collect data on worker contract completion, firm reneging on payment, and hours worked.

First, I find that worker's labor supply declines by 54 ppt for uninsured steep back-loaded contracts—which impose liquidity constraints and risk of wage theft—compared to 82% for uninsured daily pay contracts, which relax liquidity constraints and have the least losses from wage theft. Unin-

[12]The likelihood that workers are compensated by their employers increases over time, and hence their liquidity constraints get relaxed over time. By holding back wages, firms can reduce the probability that workers renege. From the worker's point of view, back-loading allows firms to extract work and then renege on the last day, resulting in losses larger than in the case where the firms would renege on a daily pay or flat contract.

[13]In a daily pay contract, the firm can refuse to pay the wages at the end of any day, in which case the worker loses the wages for the day and can break the contract for the remaining days. In a steep back-loaded contract, the due wages accumulate over time and so do the losses from potential wage theft.

[14]Firms were not informed of this treatment to avoid moral hazard.

[15]Representative of firms have to be present at work site at the end of the day to pay workers which can be costly. In the *credit* treatment we offer to pay the worker on firm's behalf.

[16]Henceforth, referred to as the matching experiment.

sured smooth contracts, which relax liquidity constraints but still impose losses from wage theft, have an acceptance rate of 40%. The gap in acceptance between uninsured smooth and steep contracts reflects a combination of liquidity constraints and the higher potential losses from wage theft in steep contracts. Workers' acceptance of jobs increases when contracts are insured against wage theft. This increase is higher and the gap is statistically significant for back-loaded contracts compared to daily pay contracts, indicating that wage theft concerns are higher for back-loaded contracts.

To isolate the effects of liquidity constraints, I compare the take-up of smooth insured contracts (which relax liquidity constraints and wage theft concerns) with steep insured contracts (which alleviate only wage theft concerns). Workers' acceptance of the former increases by 12.2 ppts compared to 42.2% for the latter. Comparing smooth uninsured and smooth insured contracts gives us the effect of wage theft concerns, which is approximately 15 ppt. A significant difference of 32.5 (27) percentage points exists between the take-up of daily pay insured (uninsured) contracts and smooth insured contracts. Since the smooth insured contracts relaxes both liquidity constraints and wage theft concerns, this result suggests that workers dislike having wages withheld for other reasons and prefer to retain the option or flexibility to break contracts. This is a novel finding and arises for two main reasons: i) workers might receive another work opportunity or face an emergency at home during the contract, leading to a loss if they break a back-loaded contract, and ii) firms may mistreat them or force them to work longer hours when wages are withheld. Overall, the 54 ppt gap between uninsured steep and uninsured daily pay contracts can be attributed to i) liquidity constraints (12 ppt or 22.2%), ii) wage theft concerns (15 ppt or 27.8%), and iii) demand for flexibility (27 ppt or 50%).

Secondly, almost 72% of the workers who reject the job offers (N=829) earn less income over the time period for which they were offered the job.[17] The average earnings of workers who rejected jobs is 27.27% lower than the offered contract. These losses are driven by rejections of steep and smooth contracts, while insurance contracts result in lower losses overall. This provides evidence of the significant effects of market failures on unemployment and welfare.

Thirdly, on the firm side, firms' demand for steep back-loaded contracts—which reduce liquidity constraints and the risk of worker reneging—is 38 ppt higher than for daily pay contracts, which have a demand of 43%. The demand for smooth contracts—which impose liquidity constraints but reduce the risk of reneging—is 67%. Therefore, 63% of the gap in demand between daily pay and steep contracts is (mostly) attributable to the higher loss from worker reneging in daily pay, while 37% is (mostly) due to liquidity constraints.[18] These effects are statistically significant. Guarantor contracts, which provide compensation against worker reneging, have a take-up rate of 69%, statistically similar to that of smooth contracts. Credit contracts, which fully alleviate firms' credit constraints and transaction costs, have a take-up rate of 89%.

Lastly, in the matching experiment, workers are 69% more likely to complete steep back-loaded

[17] 829 workers rejected the offers. We collected data on the earnings of a sub-sample of these workers, out of which 72% earned less income than what was offered.

[18] The loss to the firm from worker reneging is not necessarily identical between smooth and steep contracts, as reneging rates may vary slightly. However, since both contract types withhold some wages, these rates should be similar.

contracts than daily pay contracts (34% completion rate). This indicates back-loading effectively increases worker retention. Compared to daily pay contracts, workers with back-loaded contracts work longer hours and are more likely to report that firms require them to work beyond initially agreed-upon hours. This finding provides support for the demand among workers for the flexibility to break contracts. Non-payment by firms does not differ between the two contract types. The last outcome might have been influenced by the firms' awareness that the field team was observing their actions.

Combining the worker and firm-side experiments, I find that firm-optimal steep contracts would have a matching rate of 28%, while worker-optimal daily pay contracts would have a matching rate of 43%. If workers are provided insurance, the smooth insurance contract would have a matching rate of 55%. Workers' demand for flexibility to break contracts is the main friction, which could be reduced if firms committed to not extracting excess work or if future economic uncertainties—especially impacting the poor (Morduch (1994))—were minimized.

My results highlight the importance of labor institutions such as labor courts that can enforce contracts. These institutions can improve firm welfare in equilibrium by reducing workers' contract violations. They could also lead to welfare improvements for workers by ensuring fair compensation and protection against wage theft.[19] There are also potential efficiency gains through shifts in labor demand and supply due to increased commitment on both the worker and firm sides. Even with limited commitment, an infusion of credit can increase labor supply and demand at a particular wage. Digital platforms that enable reputation-based trust building could serve a role similar to labor courts. However, their effects may be muted by the fact that 90% of workers in my sample don't have smartphones, and only 56% have any type of phone.

In the absence of such institutions workers may develop strategies which protect them against exploitation by firms. I provide suggestive evidence for one such strategy. In a follow-up experiment, I vary whether workers are offered jobs alone or in pair with another worker. Workers are 37.5% more likely to accept jobs with back-loaded wages when paired with another worker compared to when they are offered a job alone. This suggests that workers try to reduce the possibility of facing negative costs on the job by working with others.

These results highlight how liquidity constraints and limited commitment can lead to inefficiencies in the labor market. Firms may want to hire workers but not on daily pay contracts, while workers want to work but not on back-loaded contracts. In a survey, 54% of firms wait for a trusted worker to start work, and 57% face delays in hiring new workers.[20] This can affect efficiency in two ways: through delays in starting production, and firms hiring fewer trusted workers even when they have the liquidity to hire more workers who could do the job quickly and more efficiently (if workers could commit).[21]

[19]While reputation effects could drive fraudulent firms out of the market, the arrival of new workers and incomplete information diffusion means that fraudulent firms can always find some workers.

[20]In a similar setting, Sharma et al. (2024) report that 40% firms face issues in hiring workers.

[21]Krishnaswamy (2019) shows that firms are unable to replace workers who are absent and face losses due to their absenteeism which supports the importance of our findings.

Contributions to literature This work builds on a large literature on the causes and costs of frictions in the labor markets of low and middle-income countries (Carranza et al. (2022), Bassi and Nansamba (2022), Fernando et al. (2023), Heath (2018), and reviewed in Caria et al. (2024)), the literature on theory of incomplete contracts (reviewed in Aghion and Holden (2011)) and the literature on effects of liquidity constraints on the poor (Deaton (1991), Casaburi and Willis (2018)) and informal firms (Sharma et al. (2024), Bryan et al. (2021)).

I contribute to the empirical literature by quantifying the change in labor supply when contracts are not enforceable and showing that workers have concerns about the trustworthiness of informal firms to fulfill contracts. I show that these frictions are costly, with 72% of workers who reject contract offers earning less income over the same period than the offered amount. While past research has mainly focused on firms' information asymmetry about worker productivity and moral hazard (Caria and Falco (2024), Abebe et al. (2021a)), this paper demonstrates that workers' limited commitment can also reduce firms' hiring and profits.

Economists have extensively examined household savings and consumption behavior (see Attanasio and Weber (2010)). Recent studies in developed economies (Battaglia et al. (2024), Herkenhoff et al. (2024), He and Maire (2023)) demonstrate that liquidity constraints impact labor market outcomes. This paper extends this literature by showing how these constraints influence low-income workers' contract preferences and labor supply. I also contribute to the literature on credit constraints faced by informal firms in LMICs (Islam and Rodriguez Meza (2023)). My results suggest that providing credit can increase firm's labor demand. Additionally, instant payment services could enhance efficiency by lowering firms' transaction costs, thereby boosting their labor demand. This would require that workers have access to mobile phone payment systems (Crouzet et al. (2023)).

My third contribution demonstrates two key points about low-wage informal labor markets in low- and middle-income countries: first, that worker separation rates between firms and workers are high, and second, the effectiveness of back-loading contracts in reducing these high rates. In my experiment workers renege on 66% daily pay contracts. Thus firms on average suffer a loss of around 57% of daily profits from worker reneging. This is one of the first empirical estimates of the costs of limited commitment for firms.

Literature in economics has shown that workers tend to search with friends (Caria et al. (2023)) and that workers exhibit complementarity in labor supply, particularly when commuting costs are high (Donald and Grosset (2024)). I provide suggestive evidence that this is a strategy used by workers to reduce the possibility of exploitation by firms.

Lastly, this paper provides evidence on the reasons behind simultaneous existence of high rates of unemployment and worker turnover and absenteeism in labor markets of low income countries (Breza et al. (2018), Adhvaryu et al. (2024), Banerjee and Sequeira (2023), Abebe et al. (2021b)).[22] Using a 10 day panel on labor supply and job finding rate for universe of workers arriving at the spot market, I document that unemployment can be as high as 50%.[23] In my worker side experiment, I show that

[22] Allen (1981) was one of the first papers to detail the possible reasons of worker absenteeism in ongoing jobs.

[23] This calculation is based on panel data of labor supply of all workers that arrive at the spot market over a period of 10 days. Breza et al. (2021) provides evidence on unemployment in rural agricultural markets.

workers prefer contracts which can be reneged on prior to completion without a loss (the insured daily pay contracts), to contracts which do not impose wage theft and liquidity constraints (the insured smooth back-loaded contract) but would lead to loss in wages if workers were to renege on them. Prior to the experiment, workers indicate that they have concerns about taking up back-loaded contracts due to concerns about mistreatment and exploitation by firms under these contracts and uncertainty around future shocks to health or expectation of better employment opportunities (Adhvaryu and Nyshadham (2017)). In my matching experiment, I find that workers renege on ongoing contracts in favor of staying at home due to family emergencies or to search for new jobs at the spot market. Additionally, I then show that equilibrium actions of firms justify the concerns of workers as firms extract longer hours of work from workers under back-loaded contracts. Thus, preferences for daily pay contracts, which provides flexibility to renege at the end of any day, driven by reasons cited above, explains the simultaneous existence of unemployment (due to workers rejecting back-loaded contracts at a high rate) and high worker separation (due to worker reneging). This is the first paper to show that low-income workers have a demand for flexibility break contracts.

My results also contribute to the literature on the rights of workers and their working conditions (Boudreau (2024), Boudreau et al. (2024), Naidu and Yuchtman (2013), Dube et al. (2022)). My results suggest that improvements in functioning of labor institutions could not only reduce losses for workers but also improve efficiency (Besley and Burgess (2004), Kanbur and Ronconi (2018), Roychowdhury (2014)).

The rest of the paper proceeds as follows. Section 2 describes the data I collect and the setting in detail. Section 3 lays out the theoretical framework which generates predictions that will be tested in the experiment. Section 4 lays out the details and results from the worker-side experiment. Section 5 shows the results from the firm side experiment. Section 6 includes results from the matching experiment. Section 7 concludes.

2 Data and Setting

This section outlines the primary data collected and provides a brief overview of the experiment. I then use descriptive statistics to highlight key insights about firms and workers in the labor market in my setting.

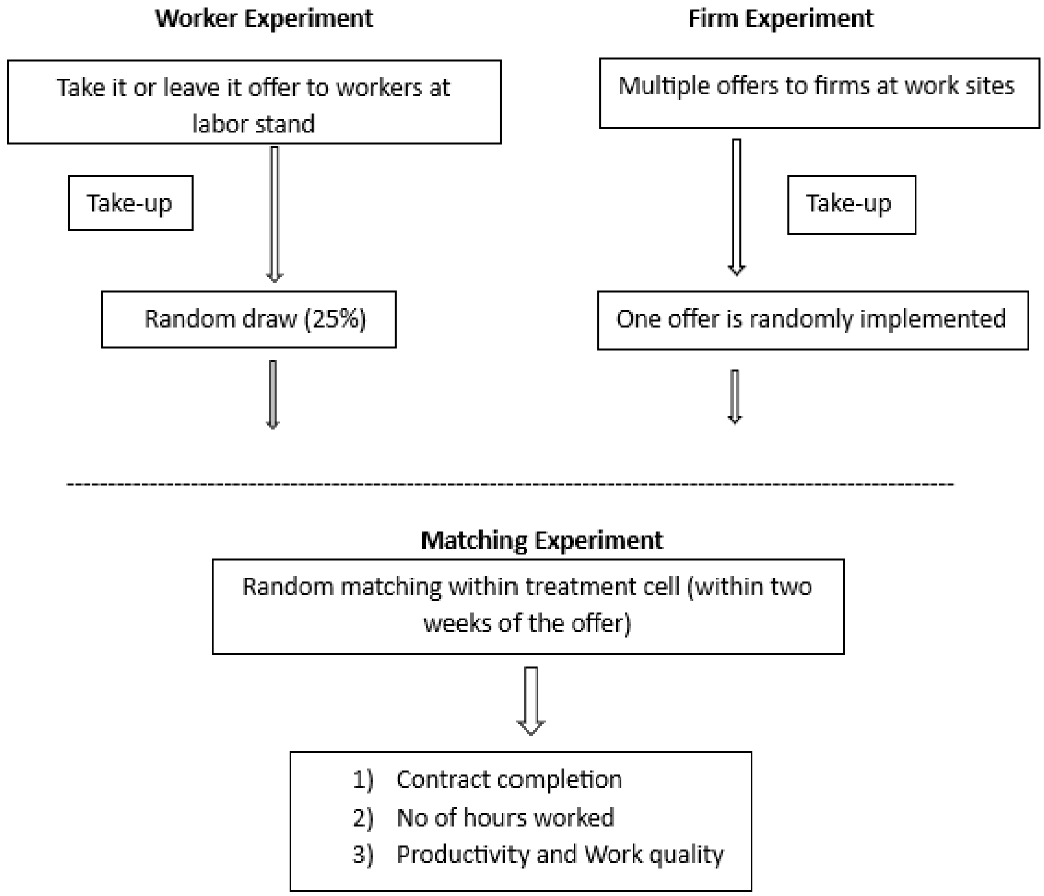
The labor market consists of firms and workers in the construction industry in Bihar, India. The construction industry employs around 57.7 million workers and contributes 8% to the GDP of India.

2.1 Data collection

My data collection exercise proceeds in four steps:

1. **Survey with firms**: I survey a sub-sample of firms to determine the most common contracts offered in equilibrium. The goal of this exercise was to create contracts which are realistic and are offered in equilibrium by the firms.

Figure 1: Experiment Design



2. **Experiment with workers**: Workers at labor stands are offered contracts (similar to the contracts offered to the firm) which vary in their payment structure. If the workers agree, I provide them a job at a site of the firm which agrees on a similar contract conditions within two weeks. A short survey is conducted after the experiment.

3. **Experiment with firms**: I conduct an experiment with firms in which they are offered to hire workers on different contracts. The conditions of contract are described to the firm, and I offer to hire a worker for them under those conditions if they agree. A short survey is conducted after the experiment.

4. **Matching experiment**: After firms and workers are matched, I observe them for the duration of the contract. I track whether firms fulfill their obligations and whether workers regularly show up at the site. I also measure worker productivity under different contracts.

A summary of the experiment design is shown in Figure 1. I shall describe each aspect of the design in the forthcoming sections.

2.2 Worker side

Workers in construction often seek work at labor stands or *chowks* in urban areas of the city. They are one of the poorest income groups in the country, with average monthly earnings of around 8000 INR per month.[24] They arrive at the stand early in the morning and firms hire them from the stand and take them to the work site. Firms and workers are aware of the locations of the labor stands in the city and this allows for a thick market to flourish at these stands.[25]

We recruit workers for our experiment from the labor stands. There are around 40 labor stands in the city of Patna. On average, there are around 180 workers searching for work at each stand daily.[26] A back of the envelope calculation suggests that around 41,000 unique workers seek work at the labor stands of Patna each month.[27] Across India, the number of workers seeking work at similar spot markets is expected to be in millions.[28] We selected 26 labor stands for our experiment. Table 1 shows the summary statistics of workers who were part of our experiment.[29]

2.2.1 Key facts

We present key facts about workers seeking employment at these labor stands. These facts are based on our qualitative fieldwork conducted before the experiment, which informed our design, as well as data collected during the experiment itself.

High unemployment and search costs at the labor stand Workers face significant search costs in our setting. On average, a worker takes 55 minutes to reach the stand. Many workers use trains, buses, auto rickshaws, boats (or a combination of these), or bicycles to reach the stand. Some walk from their homes. They spend nearly 8% of their daily wage on transportation to and from the stand. Despite spending significant resources, workers don't find work. In Appendix B-4 we plot the unemployment levels at four spot markets for a period of 7-9 days. Unemployment exceeded 50% on almost all days. This data was collected in July and August, which tend to be lean seasons in construction due to the monsoons. The sample of workers in our experiment (conducted during the peak season) worked an average of only 2.5 out of 4 days before the survey.

Worker's have concerns about wage theft Wage theft is a significant issue in the construction industry, as previously reported in Praveen (2024), Kumar and Fernandez (2015), and Wells (2023).

[24] Figure based on data collected from our experimental sample.

[25] Besides laborers, who are engaged in the work of lifting bricks, sand, mud or breaking of rocks, or preparation of concrete mix in construction, masons or bricklayers also seek work in these markets. Their job requires more skills and training compared to manual laborers. For my experiment I focus on the market of manual laborers.

[26] Figure based on data collected at each of the 40 labor stands for a period of 2 days.

[27] Based on data collected for a period of 10 days at 4 spot markets. Around 10% new workers arrive each day and the remaining worker come to the stand once every 3 days.

[28] Most Indian urban centres and towns have similar spot markets. Patna is the 19^{th} largest city in India by population. Assuming that cities bigger than Patna have a similar footfall of workers per month, then at least 760,000 workers search for work at these spot markets each month.

[29] Both men and women work in construction, though women make up a small fraction of the workforce. We found almost no women searching for work at labor stands, possibly because they use different search strategy or their families search for work as a unit. Among the women in construction, migrants form a large majority.

Wage theft can manifest in various ways. One form occurs when firms refuse to pay workers for work performed. Another happens when firms are unable to pay, perhaps due to cash flow issues, and ask workers to return later for payment. The former is a more perverse form of theft, where the firm exploits the worker's vulnerability. In such cases, workers might approach the police or relevant authorities like the labor commissioner, but the chances of being heard are often low.

12% of workers in our experiment sample had not been paid their due wages at least once in the month before the survey. The average amount due was 1209 INR, which equals wages for 2.159 days and approximately 13.4% of the monthly earnings of the workers.[30] [31] This suggests, that wage theft by firms is an important concern for the workers.

Workers face liquidity constraints for consumption purposes The daily wage in these markets at the time of our experiment was largely fixed between INR 500-550. In our experiment sample, the average daily consumption spending of the worker is $\sim$ 190 INR, which is around 35-40% of the going wage.[32] Thus an average worker would have to borrow money to consume in a steep back-loaded contract which is longer than 3 days. The 99th percentile of daily spending is approximately INR 350. Note that these consumption costs do not account for other expenses such as house rent, education and health expenses. If workers received INR 350 amount daily, it would relax the daily consumption needs of most workers.

Workers renege on contracts Reneging on contracts is common among workers. In my sample, 53% of workers know of others who have broken an oral contract without informing the firm. Workers believe this happens for several reasons: 33% think it occurs because firms ask the worker to do too much work, 18% feel that mistreatment by the firm is a reason, 60% think workers renege when they fear the firm will not pay them for the work they do, and 10% state that workers renege when they are either ill or simply do not feel like going to work.[33] This suggests that workers may have strong preferences for flexibility to break contracts (which do not back-load wages).

2.3 Firm Side

Compared to large firms that dominate the construction industry, firms in my setting are smaller. Most of these firms build houses or small office complexes in the city. Many of these firms are informal, which implies that they are not registered with the government and do not pay taxes. We recruited firms for our experiment using snowball sampling. Our initial set of firms included those which we recruited at the labor stands, and these firms provided us with contacts for other firms. Table 2 shows the summary statistics of firms which were part of my experiment.

[30] The monthly earnings are calculated by extrapolating the earnings of 1200 INR over a 4 day period.

[31] Note that this is an equilibrium figure which accounts for the precautions that workers take to avoid wage theft. 46% of the workers have previously worked with a contractor who held back payment, that is, did not pay the full wages even after the end of contract for a job, in order to make sure that the worker returns to work for the firm in the future when required.

[32] This figure only includes household spending on day to day activities, and does not include spending on education or health.

[33] Figures not shown in the table. Workers could provide multiple answers, so the percentages do not sum to 100.

Table 1: Summary stats of workers

	Mean	SD	N
Age	32.34	9.53	1,378
Years of education	4.17	4.34	1,376
Backward caste	0.71	0.45	1,378
Scheduled caste/tribe	0.24	0.43	1,378
two sided travel cost (INR)	41.40	36.76	1,332
Time to market (hrs)	0.90	0.70	1,345
Not paid atleast once (in last month)	0.12	0.32	1,318
Days not paid (in last month)	2.19	1.84	155
Non payment amount (in last month)	1,209.50	1,108.67	154
Non payment amount (in last 6 months)	2,597.10	2,687.59	230
Have worked with firm who back-loaded payment	0.40	0.49	1,318
Daily consumption cost	189.20	75.83	1,330
Others have reneged on work	0.53	0.50	1,307
Fraction days worked	0.63	0.56	1,378
Total earnings (previous 4 days) (INR)	1,198.17	874.64	1,378

The table shows summary stats of the workers who were part of the experiment. All questions were asked as part of the same survey. Number of observations may vary due to incomplete responses by workers.

Firms, on average, operate 3 construction sites and have 10 workers working under them. They are old, with nearly 14 years of industry experience. 85% of the firms are headed by contractors who were formerly masons. Only 20% of the firms are registered with the state and can be considered formal. Additionally, only 10% have a manager besides the contractor, suggesting that most firms are small. 75% of the firms in the sample hire most of their workers from the labor stands. The remaining firms are more likely to hire workers from villages.

2.3.1 Key facts

We present key facts about firms hiring workers in the construction sector below.

Firms face significant reneging by workers 79% of surveyed firms experienced at least one instance of a worker not showing up without notice in the two months preceding the survey, with an average of 5.2 such instances. This pattern of reneging influences firms' beliefs about worker reliability. Only 24% of firms believe a worker would complete a 3-day contract with daily pay, whereas 70% believe a worker would finish a 3-day contract with steep back-loaded pay.

Firms face high costs due to worker reneging When a worker reneges on a contract without notifying the firm, the firm must hire a new worker from the labor stand. This can be costly for three reasons. First, the firm spends money going to the spot market. Second, work starts late, resulting in lost productive hours for other workers who still need to be paid. Third, in some cases, work may need to stop for a day or two until a new worker is hired.

Overall, firms bear costs of around 100 INR on average if a worker does not turn up as agreed. This is around 18% of the daily wage paid to the worker, and equals the profit a firm makes from hiring one worker.[34] This suggests that search costs due to worker separation are large.

Mistrust between firms and workers can affect the firm's production and output. 54% firms state that they wait for the workers they trust to be free to start work. This implies that excessive mistrust can delay production and therefore yearly output. 56% of the firms state that they have been unable to find workers on suitable contracts or wages in the past. As the number of trusted workers may be limited this may affect firm size as well. As previous research by Chandrasekhar et al. (2020) has shown, network based hiring practices can be locally efficient but globally inefficient.

Firms face liquidity constraints 30% of employers which hire construction firms do not pay on time due to which firms face issues in paying the workers they hire. Additionally, firms also face contractual fraud by employers who hire them. Firms in my sample had faced at least one instance of non-payment by employers in the six months before the survey, with the average amount of non-payment equaling 46,000 INR or around 40% of the average monthly earnings of the firm in my sample. Thus liquidity constraints are likely to play an important role in the equilibrium behavior of firms.

Table 2: Summary stats of firms

	Mean	SD	N
Age	41.27	9.72	349
Years of education	7.17	4.30	345
Backward caste	0.72	0.45	349
Scheduled caste/tribe	0.19	0.39	349
Years working as a contractor	14.52	9.12	349
Worked as a mason before	0.85	0.36	349
Firm is registered	0.19	0.55	331
Hire most laborers from stand	0.75	0.43	253
No of workers in the firm	10.64	10.06	349
No of operational construction sites	3.23	2.34	349
Firm has a manager	0.10	0.33	331
Worker didn't turn up (in last two months)	0.79	0.68	331
Instances of worker not turning up (in last two months)	5.18	4.58	222
Instances of Employer reneging on contract	1.10	1.73	331
Amount not paid by employer	46,366.65	35,349.65	141
Costs borne if worker doesn't turn up (INR)	95.15	58.49	147
Income over last month	126,455.59	244,079.92	349
Pct. Employers don't pay on time	29.45	27.83	165

The table shows summary stats of the firm which were part of my experiment. The survey was conducted with the contractor who was the head of the firm. Individual level data corresponds to the respondent. Number of observations may vary due to non-responses or because the question was asked to only a sub-sample of firms.

The facts about firms and workers I've stated above inform my model and experiment design. Specifically, the model aims to capture the constraints faced by low-income workers and informal firms in my setting. I've designed my experiment to highlight the importance of these constraints in the labor supply and demand decisions of workers and firms, respectively.

[34] Surveys with firms show that they make around 20% profit per day on every worker they hire.

Contract design I chose contracts of two lengths greater than one day (otherwise back-loading would not be possible). To design the contract, I used a 10-day panel of job outcomes for all workers seeking employment at four labor stands, collected between July and September 2023. Among all job durations longer than one day, approximately 18% of jobs at the labor stands lasted three days (see Appendix Figure D-1b).[35] I chose a 3-day duration for the shorter contract, representing the minimum period in which worker-side concerns like wage theft and liquidity constraints would be relevant. For the longer contract, I needed a duration that differed from 3 days yet remained feasible within my budget and time constraints. Given that about 25% of all contracts (excluding 1-day contracts) offered at the labor stand last 7 or more days, I settled on 7 days for my longer contract. Wage to be paid for each day of work was determined by the prevailing market rate, which was either 500 or 550 INR.[36]

To design the payment structure for the main experiment, I first surveyed a small sub-sample of construction firms. This data was collected in May 2023. Our main experiment ran from April to September 2024. In addition to the daily pay contract, I selected two other structures (steep and smooth back-loading) and determined the wages to be paid daily for each based on my firm survey. Firms were asked to specify the total payment and payment structure at which they usually hire a worker for a job paying the firm 5000 INR over seven days. Ninety-five percent of firms stated a daily wage of either 400, 450, or 500 INR, and multiplied it by seven to arrive at the total payment.[37] The stated payment structures are illustrated in Appendix Figure D-2a. It is evident that firms back-load wages towards the latter half of the contract. Approximately 18% of firms stated a daily wage of 500 INR, while around 14% stated that they pay the entire wage on the final day. Appendix Figure D-2b shows the average daily wage for firms that do not pay 500 INR each day. Based on these findings, I decided to set a daily wage of 350 INR for all days except the last, with the remainder paid on the final day in the smooth back-loading treatment. This ensures workers do not face liquidity constraints. For the steep back-loading contract, I chose a wage of 350 INR on the first day, with the remainder paid on the final day. This mirrors the choice of firms in Appendix Figure D-2c, which favor payments on two or fewer days.

While the panel data on jobs collected at the labor stand provides information about job duration, it doesn't reveal the payment structure of contracts that worker's have worked on in the past. To ensure workers were familiar with the contracts offered in my experiment, I surveyed 108 randomly chosen workers from four labor stands. When asked an open-ended question about contract types in the construction industry, 98% mentioned daily pay contracts. Additionally, 90% and 76% reported seeing smooth and steep contracts, respectively. When specifically asked about back-loaded contracts at the labor stand, 91% confirmed that they had seen these contracts being offered at the labor stand,

[35] The high number of one-day jobs can be attributed to two main factors. First, some jobs are inherently short-term and not relevant to my sample, as firms would never hire workers for more than a day. These include fixed tasks such as unloading bricks or sand, breaking rocks, digging pits, or cleaning houses—jobs typically completed within a few hours. Second, firms occasionally hire workers for a single day to manage increased workload at construction sites where other workers are already present. Moreover, certain construction activities, like casting, must be completed in one day, prompting firms to hire workers specifically for these time-sensitive tasks.

[36] These wages exceeded the minimum wage for unskilled work in Patna, which was 392 INR during the experiment.

[37] The remaining 5% misunderstood the nature of the job and provided wages applicable to another position.

and 62% had personal experience working under such contracts. 40% workers in our experimental sample had worked in the past with a firm which back-loaded wages. This suggests that workers are indeed familiar with back-loaded contracts, indicating that the experiment's results are not influenced by unfamiliarity with these contract types.

3 Conceptual Framework

In this section, I outline a framework to help understand the preferences and actions of firms and workers under various contracts. I will use this framework to generate predictions that I will test later in the experiment.

3.1 Worker side

Worker i, has a type given by θ_i which takes discrete values and has a distribution Θ. Type captures the productivity of the worker. A firm k can hire a worker i on a contract j. A contract j for L periods is represented by $\mathcal{C}_j^L \equiv \{\omega_{\tau j}\}_{\tau=1}^L$, where $\omega_{\tau j}$ are the wages paid on day τ.

The set of contracts is given by $\mathcal{J} \equiv \{0, 1, ..., J\}$, where $j = 0$ is the opportunity to seek work at the spot market, and $j = J$ represents the opportunity of staying at home. The average daily wage for the jobs we offer in the experiment is given by $\tilde{\omega} = \dfrac{\Sigma_{\tau=1}^L \omega_{\tau j}}{L}$ and is fixed across all contracts $j \in \{1, ..., J-1\}$.[38]

Workers agree to work for H hours on each day.[39] Work beyond H hours is costly for workers, but the firm can ask the worker to do so. e_{ijt} equals the hours in excess of H for which a worker works. The firm can refuse to pay the worker if they leave the site before the firm allows them to. However, they cannot increase hours beyond a limit, $\overline{H}$.[40] This cost of effort is given by $\lambda_e e_{ijt}^2$, where λ_e is the quadratic cost parameter. For the worker, the expected cost of effort varies with the contract type. This is because the number of hours that a firm can ask the worker to work for varies with the contract type.

A worker has liquid assets given by A_{it}. As workers in our setting are extremely poor, they require liquidity for consumption purposes. When they run out of liquid assets (A_{it} falls below 0) they have to borrow and face a borrowing cost given by λ_B. Each worker starts with initial assets A_{i0} which have a distribution $\mathcal{A}$ with support $[0, \mathbf{A}]$. Workers do not want to pay the cost of borrowing, and hence they would prefer contracts that do not push their liquid assets below 0. The utility that a worker i gets on day t from working on a contract j is given by:

$$U_{ijt} = c_{it} - \lambda_B \mathbb{1}_{A_{it}<0} - \lambda_e e_{ijt}^2 \tag{3.1}$$

where c_{it} is the linear utility of consumption. As documented in the previous section worker's have

[38] Note that fixing wages across all contracts is a restriction for the purpose of generating predictions for our experiment. The total wages can of course vary across contracts.

[39] H takes the value of 8 hours per day in our setting.

[40] Above this threshold, the worker would not find it worthwhile to turn up to work the next day which would be costly for firms.

concerns about wage theft by firms. Thus workers believe that the firm they work with will pay their dues at the end of a day (in accordance with the contract) with probability q. The expected liquid assets, A_{it}, evolve as:

$$A_{it} = A_{it-1} - c_{ijt} - m_{ij} + q * \omega_{tj} \tag{3.2}$$

where q is the ex-ante probability that the wages ω_{tj} for day t under contract j are paid by firm. $q < 1$ reflects concerns about wage theft. We assume that workers don't update q upwards over the course of a contract.[41] However, they update q to 0 if they are not paid by the firm at the end of any day. This implies that workers won't return to work if they are not paid their due wages at the end of a day.

In addition to consumption, workers spend money on commuting which is given by m_{ij}. $m_{ij} = m_i, \forall j \in \{0,..,J-1\}$ and $m_{iJ} = 0$. Commuting costs capture the search costs that workers face. Workers at the spot markets spend around 8% of the daily wage, ω, in transportation to and from the stand.

Ex-ante the worker has same information about each firm, and hence $q = q^k, \forall k$. Assets cannot fall below a lower limit $-\underline{A}$. As number of periods L is small, worker borrows only once (when assets fall below 0) during this period.

I make the following assumptions about the worker's actions:

Assumption. *1. Workers require a minimum amount of consumption given by $\underline{c}_i < \tilde{\omega}$ or else they face infinite costs.*

2. Productivity of worker increases weakly in their type θ.

3. Probability of finding work at the spot market increases weakly in their type θ.

4. If the worker is not paid the agreed amount at the end of day $\tau < L$, then they break the contract on day τ.

Consumption and continuation value Workers receive a continuation value of $\Phi * A_L$ from assets at the end of period L. Thus the utility function in period L has an additional term of $\Phi * A_{iL}$, and $\Phi > 1/\rho^L$, where ρ is the discount factor. This implies that returns from saving wages above $\underline{c}_i$ (which are realized in period L) are higher than current period consumption, and therefore workers limit consumption to the bare minimum required (besides commuting costs). Thus worker consumption is given by:

$$c_{it} = \underline{c}_i, \forall i, t \tag{3.3}$$

[41] The predictions in this section would go through with a weaker assumption where workers update priors upwards within some bounds.

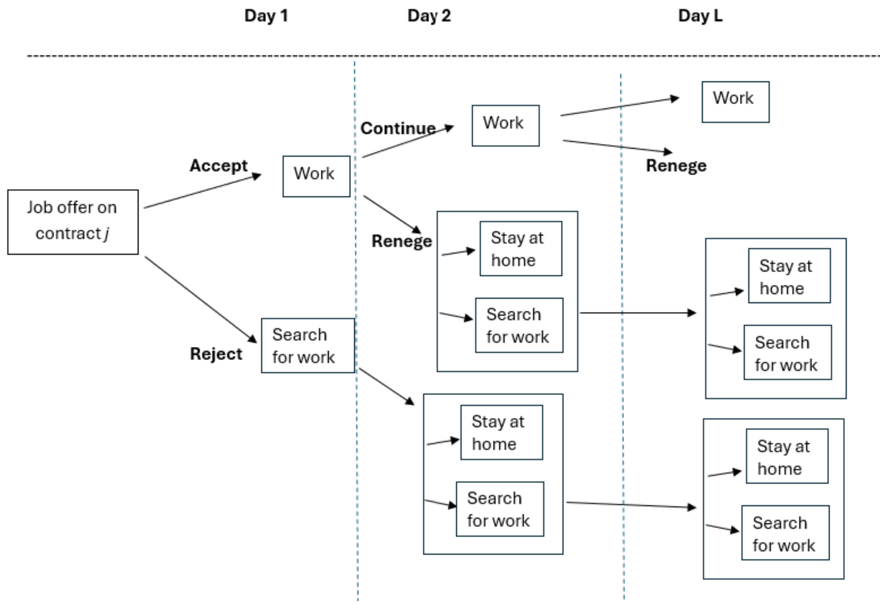


Figure 2: Worker choice

Notes: The figure shows the choices which the worker faces on each day.

Outside option The outside option of the worker on all t is to seek work at the spot market on 1 day contracts.[42] If the worker refuses a contract j offered at $t = 0$ then they seek work at the spot market on that day. From $t = 1$ till $t = L$, they have another option of staying at home. Thus worker's utility from outside option consists of their optimal choice over seeking work at the spot market or staying at home. Figure 2 shows the choices that the worker faces on each day.

Worker i finds work at the spot market with probability $p(\theta_i)$. The average expected wage at the spot market is $\omega^s > \tilde{\omega}$, the average wage under the contract j.[43] I denote the single day daily wage contract at the spot market with $j = 0$. The expected value of searching for work at the spot market in one period is given by:

$$U_{iot} = \underline{c}_i - \lambda_B \mathbb{1}_{A_{it}<0} - p(\theta_i)\lambda_e e_{i0t}^2 \tag{3.4}$$

Here, $p(\theta_i)$ captures the expectation as effort is exerted only if the worker finds a job. Asset evolution is governed by the following equation:

$$A_{it} = A_{it-1} - \underline{c}_i - m_{ij} + p(\theta_i) q_0 \omega_{tj} \tag{3.5}$$

where q_0 is the probability that worker doesn't get paid.

[42] This assumption captures the fact that workers are offered contracts only on $t = 0$ in our experiment. It is possible that they receive job offers on contracts similar to ours by other firms, but I disregard those possibilities for ease of exposition.

[43] The inequality captures the fact that job opportunities at the spot market are a mix of jobs which offer wage $\tilde{\omega}$ for the day and others which offer more than that.

The value of staying at home is given by:

$$U_{iJt} = \underline{c}_i - \lambda_B \mathbb{1}_{A_{it}<0} + \mu_J \tag{3.6}$$

where μ_J is parameter which captures value of staying at home.

Reneging on contracts Figure 2 captures the choices that worker faces each day. The data we collected from the firms and workers suggests that limited commitment on the worker side is a significant issue in informal markets. We model this by giving the worker an option to renege on the contract after each day. This decision (denoted by $d_{it} \in \{0,1\}$) is based on the comparison between the remaining value of the contract and the value of their outside option. $d_{it} = 1$ represents the choice to continue with the contract. If $d_{it} = 0$ in some time t then the worker cannot return to the contract and makes the choice between spot market or staying at home for the remainder of the period L.

3.1.1 Value of contracts

The value of continuing with a contract $j \in \{1, ..., J-1\}$ to worker i at time t if the firm had paid the dues in the previous time period is given by:

$$V_{ij}^t(A_{it}, e_j) = U_{ijt} + \epsilon_{ijt} + \rho\{q * \mathbb{E}\max_{d_{it+1}}[d_{it+1} * V_{ij}^{t+1}(A_{it+1}, e_j) + (1-d_{it+1})V_{ir}^{t+1}(A_{it+1})] + (1-q) * V_{ir}^{t+1}(A_{it+1})\} \tag{3.7}$$

where A_{it} is the liquid assets of the worker, ρ is a discount factor.[44] ϵ_{ijt} is the idiosyncratic shock which have a Type-1 extreme value distribution and are $i.i.d$ across i, t. The realization of the shock is same across all contracts for workers. Hence, the same shock has a higher value when the worker's assets at the end of any day is high (or conversely money withheld by firms is low).

$V_{ir}^{t+1}(A_{it+1})$ is the value of reneging on the contract at the beginning of time period $t+1$, and $V_{ij}^{t+1}(A_{it+1}, e_j)$ is the future value of continuing with contract j.

The value of reneging on any contract $j \in \{1, ..., J-1\}$ to worker i at time t is given by:

$$V_{ir}^t(A_{it}) = \max\{V_{i0}^t(A_{it}), V_{iJ}^t(A_{it})\} \tag{3.8}$$

where $V_{i0}^t(A_{it})$,$V_{iJ}^t(A_{it})$ is the value of searching at the spot market or staying at home respectively and given by:

$$V_{i0}^t(A_{it}) = U_{i0t} + \epsilon_{i0t} + \rho\mathbb{E}V_{ir}^{t+1}(A_{it+1}) \tag{3.9}$$

[44] In our setting, experimental data suggests that temporal decisions are not driven by discounting of future payoffs over a relatively short period of time. Thus, the discount rate plays a minor role. I assume an annual interest rate of 5 percent, and the daily discount rate $\rho = 1/(1+0.05/365)$.

$$V_{iJ}^t(A_{it}) = U_{iJt} + \epsilon_{iJt} + \rho \mathbb{E} V_{ir}^{t+1}(A_{it+1}) \tag{3.10}$$

Value of accepting or rejecting a job offer Value of rejecting a job offer j is given by:

$$V_{i0}(A_{i0}, a_i = 0) = U_{i00} + \epsilon_{i00} + \rho \mathbb{E} V_{ir}^{t+1}(A_{it+1}) \tag{3.11}$$

Two points are worth noting in Equation 3.11. Firstly, after rejecting the contract the worker continues to seek work at the spot market for the day 0 and secondly, their choices are restricted to spot market ($j = 0$) or staying at home ($j = J$) after that. Value of accepting a job offer j is given by:

$$V_{ij}(A_{i0}, a_i = 1, e_j) = U_{ij0} + \epsilon_{ij0} + \rho \{ q * \mathbb{E} \max_{d_{it+1}} [d_{it+1} * V_{ij}^{t+1}(A_{it+1}, e_j) + (1 - d_{it+1}) V_{ir}^{t+1}(A_{it+1})] + (1 - q) V_{ir}^{t+1}(A_{it+1}) \} \tag{3.12}$$

Next, I delve into the decision making for the firms, after which I describe equilibrium actions of workers and firms.

3.2 Firm Side

Firm k hire workers i on different contracts $j \in \{1, ..., J-1\}$. Firms don't observe worker type θ at the time of hiring them. Firms face search costs λ_s when they have to hire a new worker. This cost represents a combination of money spent in going to the spot market to find a worker and the value of time they lose in that process.

79% of firms in our sample reported that they faced at least one instance of worker reneging in the two months prior to our survey. Therefore, in the model, firms believe that workers who are employed under contract j can renege on the contract with probability r_j. The liquidity distribution for firms is given by $\mathcal{B}$. Firms choose the number of excess hours that the worker has to work under each contract (given by e_j). Firms don't fire workers after employing them. The only choice that firms make is the number of hours beyond H that a worker works for in contract j, given by e_j.

The period profit function of the firm is as follows:

$$f_{kjt} = \mathbb{1}_{t=L} * B_{kt} - \omega_{jt} - \lambda_s - \lambda_{pf} \mathbb{1}_{\omega_{jt} > 0} - \lambda_f * \mathbb{1}_{B_{kt} < 0} \tag{3.13}$$

$$M = \Sigma_L \nu \widehat{\theta}(H + e_{kj}) \tag{3.14}$$

where $\widehat{\theta}$ is mean of the worker type, ν is the value that the firm generates per hour of work. ω_{jt} is the wage paid on day t under contract j. As documented in the previous section, firms in our setting are liquidity constrained and face borrowing costs, λ_f, if the liquid assets dwindle below 0. λ_{pf} is the transaction cost that firm incurs and represents the cost incurred by the firm for staying at the site to pay the worker at the end of the day. e_{kj} is the number of hours of work (beyond H) that a firm k asks the worker to do in contract j. M is the total value that the firm gets from the contract.

The firm's contracts with its employers is back-loaded, implying that payment occurs after the start of work. The firm is compensated for this value by its employers on any day with probability g_t, where g_t increases in t and $\Sigma_L g_t < 1$.[45]

I assume that firm' assets evolve for the period L as :

$$B_{kt} = B_{kt-1} - \omega_{jt} + M * g_t \tag{3.15}$$

The value of hiring a worker on contract $j \in \{1, ..., J-1\}$ in the experiment on day t is given by:

$$\Pi_j^t(B_{kt}, r_j) = f_{kjt} + \lambda_s + \eta_{kjt} + \rho\mathbb{E}[(1-r_j)\{\Pi_j^{t+1}(B_{kt+1})\} + r_j\Pi_{0k}^{t+1}(B_{kt+1})] \tag{3.16}$$

where η_{kjt} is a Type-1 extreme value error which is independent in k, t and $\Pi_{0k}^{t+1}(B_{kt+1})$ is the value of hiring a worker from the outside option. Note that the firm doesn't bear search cost when they hire a worker offered in the experiment because the field team takes the worker to the work site on the first day. The firm's outside option is given by:

$$\Pi_{0k}^t(B_{kt}) = F_{kt} + \eta_{k0t} + \rho\mathbb{E}[\Pi_{0k}^{t+1}(B_{kt+1})] \tag{3.17}$$

Note that the outside option is different for each firm and is determined by the function F_{kt}. This captures firm's resources and networks which allow it to hire workers. F_{kt} is a one to one mapping of the firms' initial assets, B_{k0}.

Wage stealing by firms Till now, we have modeled firms which are honest and pay the worker their dues as per the contract. Firms which intend to defraud workers are also present in the spot markets. Their presence influences the parameter q, the worker's belief that they will be paid, in the model. How do such fraudulent firms act under different contracts? Firstly, such firms would be willing to hire a worker on any contract. Note that a worker will renege with probability 1 if the firm reneges on payment on any day. Therefore, in a daily pay contract, a fraudulent firm will steal wages on the first day. This is because the worker might renege after the first day with a positive probability, which would not give a chance to firms to steal wages. In a back-loaded contract, the decision of the firms is more complicated. There are two competing forces which push the decision to steal in opposite directions. As wages are withheld, the firms can steal higher wages by reneging on the last day. But the likelihood that the worker reneges before that might push the firm to renege before the last day. Thus the time when the firm reneges is a function of the firm's prior about r_j.

3.3 Equilibrium

Firms choose e_j^k, the number of excess hours that a worker works for in contract j, and workers choose d_{it}^j, whether they want to renege on a contract j or not. For the worker, an increase in e_j^k,

[45] The timing of the process is as follows. A firm will start work at a site by hiring workers. It will decide the number of hours of work based on the contract j which will generate a total value of M. The firm will be compensated this value by its employers on any day t with probability g_t. The firm will pay the workers during the week based on the agreed contract by using its own liquid assets or borrowing.

increases the probability of them reneging. While firms want to increase e_j^k (with an upper bound of $\overline{H} - H$), they risk an increase in rates of reneging.

Worker's decision problem A worker makes a choice to accept a contract j over their outside option. This choice is independent across all contracts. The worker's decision problem when offered a contract j is given by:

$$W_i^j(\omega) \equiv \max_{a_i, \{d_{it}\}_1^{L-1}} a_i * V_{ij}(A_{i0}, a_i = 1, e*_j) + (1 - a_i) * V_{i0}(A_{i0}, a_i = 0, e*_j) \tag{3.18}$$

$$s.t. \quad e*_j = \int_k e_j^k \, \mathrm{d}\mathcal{B}(k) \tag{3.19}$$

where a_i^j is the worker i's choice to take up a contract j, given firm's choice $e*_j$.

Firm's decision problem The firm's decision problem when hiring a worker on contract j is given by:

$$T_k^j(\omega) \equiv \max_{b_k^j, e_j^k} b_k^j * \Pi_j^0(B_{k0}, r*_j) + (1 - b_k^j) * \Pi_0^0(B_{k0}, r*_j) \tag{3.20}$$

$$s.t. \quad r_j = \int_i d_i^j \, \mathrm{d}\mathcal{A}(i) \, \mathrm{d}\Theta(i) \tag{3.21}$$

where b_k^j is firm k's choice to hire a worker on contract j, given worker's choice r_j.

Definition. ***Equilibrium**: Given parameters $\{\rho, q, \lambda_s, \lambda_B, \lambda_f, \lambda_{pf}, \lambda_e, \nu\}$, worker type distribution Θ, worker asset distribution $\mathcal{A}$, firm asset distribution $\mathcal{B}$, and value functions $V(.), \Pi(.)$, an equilibrium in contract j is a vector $\{e*_j, \{b^j\}_k, r_j, \{a^j\}_i\}$ such that worker's make optimal choice in 3.18, firm's make optimal choice in 3.20 and the priors match the equilibrium behavior (3.21, 3.19).*

3.4 Predictions from the model

I use the model to generate predictions about the behavior of firms and workers in the labor market. This includes predictions about the preferences of firms and workers over different contracts as well as the actions they take in equilibrium after being matched with each other. My empirical analysis will be guided by these predictions.

Definition.
1. *A daily pay contract denoted by $\mathcal{C}^{\mathcal{D}}$ is one which pays the worker the same amount daily: $\{\omega\}_{\tau=1}^L$*
2. *A smooth back-loaded contract denoted by $\mathcal{C}^{\mathcal{S}m}$ is one which pays the worker the same amount for all days except the last day, and $\omega_i < \omega_L, \forall i < L$.*
3. *A steep back-loaded contract denoted by $\mathcal{C}^{\mathcal{S}}$ is one which pays the worker only on the first and the last day, and $\omega_1 < \omega_L$.*

The total payment made across the three contracts of the same length is the same. Our experiment will cross-randomize these three contracts with zero insurance contracts, which shift q to 1.

The probability that workers accept a contract j which pays an average daily wage of $\tilde{\omega}$ is given by $P(j)$ where

$$P(j) = \mathbb{E}[\mathbb{1}.\{\mathbb{E}[V_{ij}(A_{i0}, e*_j)] \geq \mathbb{E}[V_{i0}(A_{i0}, e*_j)]\}] \tag{3.22}$$

where the outer expectation is taken over a joint distribution of $(\Theta, \mathcal{A})$. Equation 2.15 implies that workers probability of agreeing to work on a contract depends on the expected value of the contract as compared to expected value from searching at the spot market.

Worker side

Prediction. ***W.1***: *The probability of accepting a contract of length L with same average daily wage $\tilde{\omega}$, where $\tilde{\omega} > \omega_1^{\mathcal{C}^{Sm}} = \omega_1^{\mathcal{C}^S} > \underline{c}_i$, weakly declines in the steepness of back-loading, that is, $P(\mathcal{C}^{\mathcal{D}}) \geq P(\mathcal{C}^{Sm}) \geq P(\mathcal{C}^S)$*

A daily pay contract is *worker optimal* (among the three contracts I described) as it doesn't impose liquidity constraints and poses the least wage loss risk to the worker which provides them the maximum flexibility. Among all contracts, the optimal contract for firms (assuming that workers face no constraints) would be one that pushes payment of all wages to the last day.

Prediction. ***W.2***: *If q, the worker's ex-ante belief that a firm is honest, increases, then probability of accepting a contract (keeping L and $\tilde{\omega}$ the same) increases, that is, $P(j_{q1}) \geq P(j_{q2})$, where $q_1 > q_2$.*

Prediction. ***W.2.1***: *For a smooth contract, providing insurance, that is shifting q to 1, increases the take-up.*

This prediction tells us that wage theft concerns affect the preference over contracts of workers.

Prediction. ***W.3***: *If $q = 1$, that is workers don't have concerns about wage theft, workers are more likely to accept smooth contracts compared to steep contracts due to liquidity constraints.*

Prediction. ***W.4***: *Workers are more likely to accept daily pay insured contracts than smooth insured contracts, due to a demand for flexibility to break contracts.*

This predictions implies that workers are more likely to accept daily pay contracts which are insured against wage theft, compared to smooth contracts which are insured against wage theft. This difference captures the fact that workers want the flexibility to break contracts without loss which is available to them in a daily pay contract but not in a back-loaded contract.

Prediction. ***W.5***: *High type workers are less likely to accept a contract j, that is, $P(j|\theta_1) \leq P(j|\theta_2), \forall \theta_1 > \theta_2$.*

This prediction captures the fact that workers which have high type have better outside options which leads them to reject the contracts at a higher rate.

Prediction. ***WE.1***: *In equilibrium, workers renege at a higher rate in daily payment contracts (C^D) than steep contracts (C^S) with same length L and average daily wage $\tilde{\omega}$.*

Firm side The probability that firms are willing to hire a worker on a contract j which pays an average daily wage of $\tilde{\omega}$ is given by $P_f(j)$ where

$$P_f(j) = \mathbb{E}[\mathbb{1}.\{\mathbb{E}[\Pi^0_{kj}(B_{k0})] \geq \mathbb{E}[\Pi^0_{k0}(B_{kt})]\}] \tag{3.23}$$

where the outer expectation is taken over the distribution of $\mathcal{B}$.

Prediction. ***F.1***: *The probability of hiring a worker on a contract of length L with same average daily wage $\tilde{\omega}$ weakly increases in the steepness of backloading, that is, $P_f(\mathcal{C}^{\mathcal{D}}) \leq P_f(\mathcal{C}^{Sm}) \leq P_f(\mathcal{C}^{S})$.*

The steep backloaded contract is *firm optimal* (among the three contracts I described) as it doesn't impose liquidity constraints and has the least probability of worker reneging, thereby reducing separation costs for the firm.

Prediction. ***F.2***: *Providing credit to firms increases their probability of hiring workers.*

Prediction. ***F.3***: *Providing compensation to firms if worker reneges on a contract increases their probability of hiring a worker.*

Prediction. ***FE.1***: *In equilibrium, firms ask workers to work for longer hours on steep contracts compared to daily contracts with same length L and average daily wage $\tilde{\omega}$.*

All proofs are in Appendix Section A.1.

3.5 What would an optimal contract look like?

Given that firms and workers have opposing preferences for different contracts it's important to understand what contract a social planner could implement to maximize welfare. The instrument available to the social planner would be the set of all possible contracts with fixed average daily wage $\tilde{\omega}$. This subsection will try to sketch out the structure of a welfare-maximizing contract.

The social welfare is given by the sum of worker and firm welfare:

$$\text{Welfare}^j(\tilde{\omega}) = \int_i W^j_i(\tilde{\omega}) + \int_k T^j_k(\tilde{\omega}) \tag{3.24}$$

where $W^j_i(\tilde{\omega})$, $T^j_k(\tilde{\omega})$ are as defined in equation 3.18 and 3.20. Two factors influence welfare under each contract. The first is the matching rate, and the second is the cost of search, which is affected by the extent to which each contract can reduce reneging rates.

We begin by analyzing the problem of designing an optimal contract in the absence of limited commitment or liquidity constraints on either side of the market. When ρ approaches 1, all payment structures yield the same level of welfare. Next, we will examine this problem by introducing one constraint at a time to explore their individual effects on the optimal contract design.

Optimal contract in the presence of only worker side limited commitment When workers can't commit due to presence of outside options, then firms face losses when they renege. Welfare maximization then involves minimizing reneging by the worker. To achieve this, the social planner would back-load all wages to the last day of the contract.

On top of this, if firms face liquidity constraints as well, then optimal contract would remain unchanged as the contract which back-loads all wages to the last day imposes least liquidity constraint on the worker.

Turning on worker-side constraints In addition to the two firm-side constraints, let's add worker side liquidity constraint to the problem. To reduce worker disutility from borrowing the social planner would want to shift some wages to the early parts of the contract. This would come at the cost of increasing firm borrowing. The optimal contract under this constraint (along with the two firm-side constraint) would pay some wages to the worker in the earlier parts of the contract.

What would an optimal contract look like when the last constraint – firm side reneging – is turned on? With this constraint, worker would want that a larger share of the payment is made to them in earlier parts of the contract so as to reduce their risk from wage theft and excess work exaction by firms. The social planner would be willing to reallocate the wages to earlier parts of the contract as the higher matches that such a reallocation would achieve would compensate the increase in borrowing and reneging costs for firms.

In conclusion, a welfare-maximizing contract would structure payments by providing some wages during the early stages of the agreement while deferring the majority of the compensation to the final day. Although this approach would not perfectly replicate a smooth contract, it would most closely resemble the shape of a smooth contract compared to the other two contracts examined in the experiment.

4 Worker Side experiment

The experiment was conducted at labor stands in Patna between April and September 2024.

4.1 Recruitment and design

Worker recruitment We surveyed workers at the labor stand and offered them jobs based on their treatment, which was determined randomly through a list of unique IDs. Enumerators, who were randomly assigned these IDs, approached workers at the labor stand. Starting with the first ID assigned to them, they proceeded down the list. Since each ID corresponded to a treatment cell, the treatment assignment for each worker was random. Enumerators were unaware of the treatment associated with each ID prior to the survey. Each worker was offered a job at a construction site near the stand, with their contract determined by the treatment assignment. To ensure consistency across all workers and contract types, they were not informed of the exact location of the site at the time of the offer. Workers were, however, told that the site would be close to the stand, and we would escort them there on the first day of work.[46] All workers were offered the same job, for which

[46]This procedure mimics the behavior of firms hiring workers from the labor stand.

the prevailing wage at the labor stand is relatively fixed.[47] The job required workers to assist masons with bricklaying, which is the most common task for which firms hire workers in construction.

Each worker was offered two jobs, one for each of the different contract lengths.[48] The order of the job offers was randomized. If the worker accepted the job offered, then the contract was executed with a 25% probability through a random draw. This information was given to them prior to offering the job. As there is a positive probability of being allotted any job, workers' choice should be incentive compatible.[49] The probability of being allotted the job post acceptance was independent (and equal to 25%) across the two offers. They were informed about the outcome of the random draw at the end of the survey. In addition to the job offer, workers were administered a short survey.

To prevent spillovers, enumerators were instructed to make job offers a short distance away from the labor stand. Job offers were made between 7:30 a.m. and 10:30 a.m. over two to four consecutive days at a labor stand. The number of days for continuous hiring depended on the size of the labor stand, which varied. In some cases, particularly at larger stands, the field team returned after a one-week gap. To avoid making duplicate job offers to the same worker on different days, we uniquely identified workers using their names, age, and village name.[50] Enumerators were also instructed to confirm with the worker whether they had previously been offered a job. Workers were informed that jobs would be provided to them within two weeks of the offer. The firm-side experiment was conducted concurrently by a separate field team. However, due to uncertainty around labor demand, it was not always possible to provide jobs to workers on the same day as the offer. Further details on the implementation can be found in Appendix F.1.

Experiment Design I design the experiment to tease apart three frictions — concerns for wage theft, liquidity constraints and demand for flexibility — which affect the labor supply of workers.

My experiment has the following cross-randomized treatments (shown in Figure 3):

1. **Payment structure of Contract:** Workers and firms are offered contracts with three payment structures.[51]

    - Steep back-loading: 350 INR being paid on Day 1 and the remaining payment ($3*W-350$ INR for a 3 day contract, and $7*W-350$ for a 7 day contract) being made on the last day.[52]

[47] The existence of wage floors has been documented in previous work by Breza et al. (2019).

[48] The first 300 workers we surveyed were offered a three-day job, while the remaining workers were offered two jobs. This process was pre-registered.

[49] I introduced randomization in contract execution to increase the sample size of the survey without having to increase the number of firms (which is a constraint) or the time period between the survey and job offer (which might make the choice of workers less realistic).

[50] This data was provided to the field supervisors through an online tool which was deleted after completing the survey.

[51] The total wages offered to workers across the three contracts is the same. There might be concerns that discount factor may lead to lower valuation of back-loaded contracts. To check if this was the case, I ran a small pilot where I offered workers two back-loaded contracts with the same payment structure, except that the total payment was larger and accounted for a daily discount factor of 0.96 in one of the arms. The difference in take-up of the two contract was close to zero which suggests that discounting is not relevant given the short length of the contracts.

[52] W denotes the going wage in the spot market. This was either 550 or 500 INR at the time of the experiment.

Figure 3: Treatment Cells and Sample size

Cell	Days			Days	
	3	7		3	7
No insurance, No backloading	9%	6%	Insurance, No backloading	6%	4%
No insurance, smooth backloading	12%	8%	Insurance, smooth backloading	12%	8%
No insurance, steep backloading	9%	6%	Insurance, steep backloading	12%	8%

Notes: The total sample size is 1378. Out of these the first 300 workers were offered just one job for 3 day contracts. The remaining workers were offered two jobs.

- Smooth back-loading: 350 INR paid on each except the last day, and the remaining payment being made on the last day.
- Daily Payment: Workers are paid INR W at the end of each day.

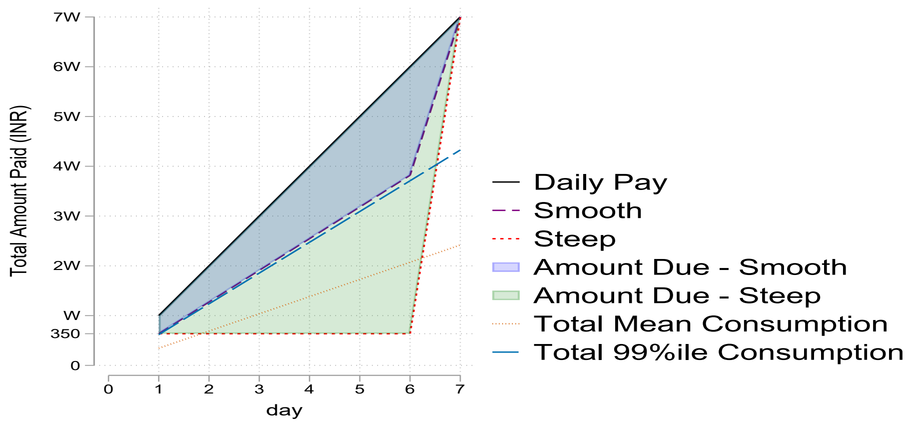
2. **Insurance vs No insurance:** A random sub-sample of workers was offered zero cost insurance against wage theft. Workers were told that we will pay them their due wages in case the firm reneges on its payment. For ethical reasons, workers who accepted the no insurance contract but were not paid by the firms, were compensated as well, but they were not given this information before accepting the contract. The insurance contract was provided in writing and had the signature of the survey firm.

3. **Length of contract:** We offered contract of two lengths, 7 days and 3 days.

The insurance treatment arm replaced trust in the firm with trust in the survey firm. I assumed that providing a written insurance guarantee, which firms do not offer, would increase the worker's trust in us. This method helps estimate the lower bound of concerns about wage theft in job acceptance. To gauge worker trust in the survey firm, we ask workers why they accept or reject contracts. This helps us estimate how many would accept insurance contracts if they trusted the survey firm. A total of 1378 workers were surveyed. The sample size for each treatment cell is shown in Figure 3.

Separating effects of wage theft, liquidity constraints and flexibility: My experiment design allows us to separate the effects of wage theft concerns, liquidity constraints and demand for flexibility on take-up. Figure 4 highlights the constraints imposed by different payment structures on workers. A steep contract imposes all three constraints on the worker. A smooth contract relaxes liquidity constraints by paying the worker 350 INR daily, which exceeds the 99%ile of the daily consumption stated in the survey. An insurance contract reduces wage theft concerns to zero. A daily payment contract relaxes liquidity and flexibility constraints, but might have some wage theft constraints (at the end of day 1). An insured daily pay contract relaxes all constraints. Figure 5 details how I will disentangle the three effects.

Figure 4: Constraints under different contracts

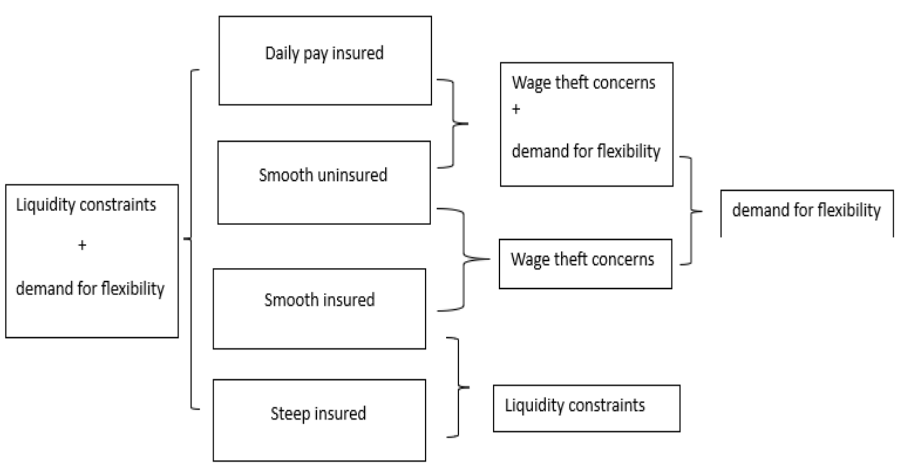


Notes: The figure shows the amount paid to workers under different contracts, and the constraints that each contract imposes on workers. W indicates the wage paid for each day of work. Total mean consumption indicates the average total daily consumption till a particular day for the workers in the sample. Total 99%ile consumption maps the same figure for the 99 %ile of worker in the sample. Amount due on any day is the total amount that remains to be paid by the firm to the worker for services already rendered.

The increase in take-up under a smooth insured contract over a similar contract with no insurance will provide us the estimate of the effect of wage theft concerns on take-up of contracts. This tests **Prediction W.2.1** from the model. Providing insurance on smooth and steep contracts removes wage-theft concerns. Assuming that demand for flexibility is orthogonal to steepness of contract, the difference in take-up between smooth insured contract and steep insured contract will give us effect of liquidity constraints on take-up. This tests **Prediction W.3** from the model.

The take-up of smooth back-loaded contracts under insurance, compared to take-up of daily pay contracts with insurance gives us the effect of demand for flexibility. This tests **Prediction W.4** from the model.

Figure 5: Worker side identification



4.2 Results

My primary specification is shown in equation 4.1.

$$
\begin{aligned}
Y_i = \alpha + \beta_1 * \textit{Daily Pay} + \beta_2 * \textit{Smooth} + \beta_3 * \textit{insurance} + \beta_4 * \textit{Daily Pay} \times \textit{insurance} \\
+ \beta_5 * \textit{Smooth} \times \textit{insurance} + X_i + \mu_i + \epsilon_i
\end{aligned}
\tag{4.1}
$$

X_i indicate controls — worker age, education, and half hour of survey time— and μ_i includes fixed effects for the labor stand and length of the contract.

Figure 6 tests Prediction W.1. 28% workers accept an uninsured steep back-loaded contract and 40% accept an uninsured smooth contract. Appendix Figure B-1 shows the decomposition for 3- and 7-day contracts. Steep uninsured contracts have acceptance rates of 36% and 17% for 3 and 7 days, respectively, while smooth contracts have a 40% take-up rate for both durations. These rates are significantly lower compared to the 82% take-up of daily pay contracts (80% for 3 days and 84% for 7 days).

I collected data on potential earnings of workers who rejected the contracts (see 4.2 for more details). Using this data, I calculate the average daily earnings of workers who rejected the contracts. Assuming workers earn this amount daily, the daily discount rates that would rationalize their decision to reject smooth and steep contracts are: i) Smooth (3-day): 0.21 ii) Smooth (7-day): 0.43 iii) Steep (3-day): 0.51 iv) Steep (7-day): 0.83. Taking the monthly money lending rate from loan sharks as 25%, the daily discount factor should be around 0.9917. Thus the calculated discount rates are far too low to explain workers' choices. Therefore, frictions arising from the payment structure are more likely to explain these preferences.

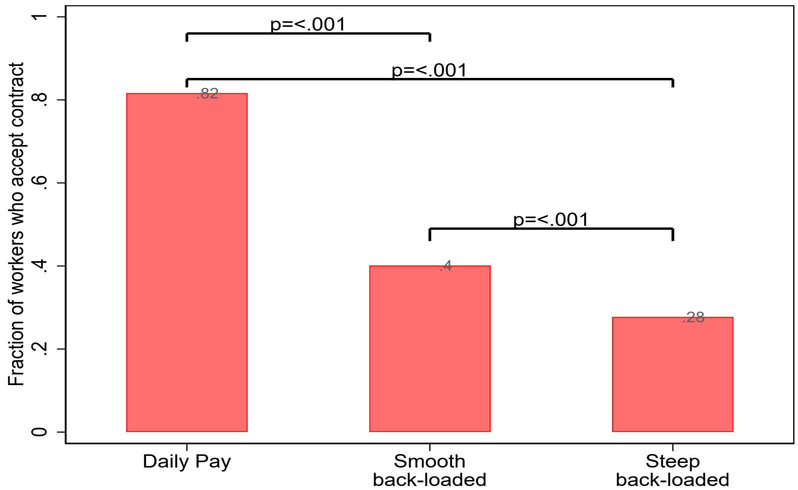
Next, in Figure 7 I look at how concerns about wage theft affect the labor supply. I pool smooth and steep contracts into one category of back-loaded contracts. Take-up of jobs which have insurance is higher by 6 ppts for daily pay contracts. This rises to 14 ppts for back-loaded contracts. These two results together show that Prediction W.2 is correct. Additionally, the difference in difference of the take-up between insured and uninsured daily pay and back-loaded contracts is significant (p-val = 0.037) which suggests that wage theft concerns are more relevant for back-loaded contracts as the amount due in a back-loaded contract at the end of any day is higher (see Figure 4). The insurance contract serves as a substitute for a third party acting as a guarantor of payment (provided evidence of fraud can be given), mimicking the role that a labor court would play.[53]

Prediction W.5 states that take-up of contracts decreases in worker type. I test this in Figure 8. Workers who are in the top decile of income earned (over the four days prior to my survey) are categorized as high type.[54] This measure was pre-registered. These workers are 12 (17) ppt less likely to take up a daily pay (back-loaded) job than workers below the 90%ile. Note that these workers are actively seeking work at the labor stands. The difference in take-up between types is more pronounced for back-loaded contracts than for daily pay contracts (p-val = 0.09). This may be

[53] Note that when offering the insurance contract, workers were informed that shirking at work would disqualify them from coverage. This condition was intended to prevent any moral hazard under third-party insurance.

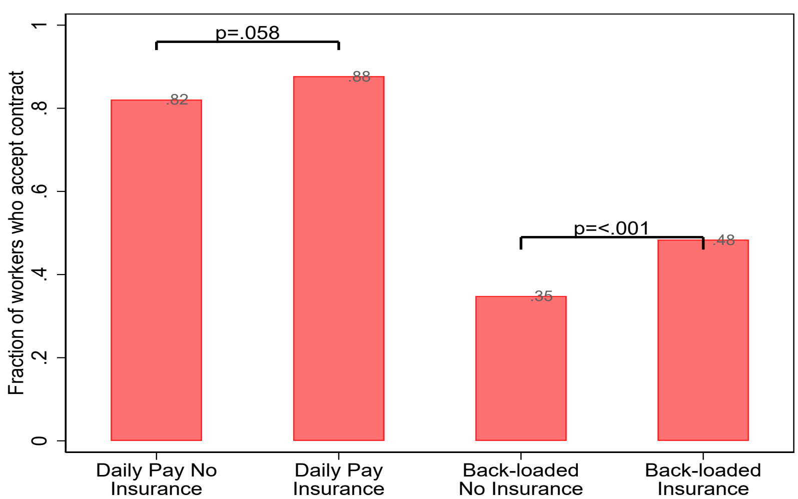
[54] Alternate measures for type, such as including those in the top quartile, give us similar results.

Figure 6: Take up of uninsured daily pay vs back-loaded contracts



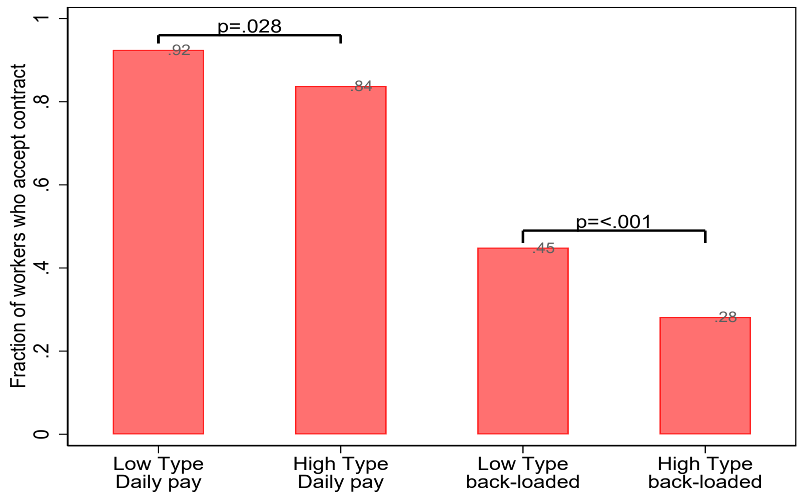
Notes: The figure shows coefficients from regression 4.1 for uninsured contracts. I use fixed effects for the labor stand and length of contract, and control for respondent age, education and half hour of survey. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

Figure 7: Effect of insurance on take-up of daily pay and back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for comparison between insured and uninsured contracts. I pool steep and smooth back-loaded contracts for ease of representation. I use fixed effects for the labor stand and length of contract, and control for respondent age, education and half hour of survey. The p-value of difference in difference test between take-up of daily pay and back-loaded contracts for uninsured vs insured contracts is 0.037. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

Figure 8: take-up of daily pay and back-loaded contracts by worker type



Notes: The figure shows coefficients for take-up of daily pay and back-loaded contracts by worker type. I pool steep and smooth back-loaded contracts for ease of representation. I use fixed effects for the labor stand, length of contract, whether the contract was insured and control for respondent age, education and half hour of survey. The p-value of difference in difference test between take-up of daily pay and back-loaded contracts for uninsured vs insured contracts is 0.09. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

because high-income workers tend to have higher productivity, making the loss from potential wage theft or forgone opportunities in back-loaded contracts greater than for low-type workers.

In Appendix Figures B-1, B-2, I show the take-up for all 12 treatment cells separately.

Decomposing the effect of different frictions Until now, I have tested workers' labor supply across different payment structures and examined how insurance affects these preferences. Next, I decompose these preferences to explore the extent to which various frictions—concerns about wage theft, liquidity constraints, and demand for flexibility—impact labor supply. I assess these frictions using the comparisons described in Section 4.1 and Figure 5.

Table 3 disentangles the effect of wage theft concerns, liquidity constraints and demand for flexibility on take-up of job offers. There is no statistically significant difference between take-up of smooth insured and steep insured contracts for three day treatment. Therefore, consumption liquidity constraints are not relevant for short periods. However, there is a significant difference in take-up between these contracts for seven days, which suggests that these constraints become important over longer time periods. Thus, Prediction W.3 holds for contracts which are 7 days long.

Wage theft concerns reduce the take-up of jobs by 37.5%, and this result holds for both short (3-day) and long (7-day) contracts. This verifies Prediction W.2.1. The striking result from Table 3, which confirms Prediction W.4, is that workers have a significant demand for contracts that offer flexibility to renege, with take-up of inflexible jobs that relax credit and wage theft concerns being 34 percentage points lower than flexible jobs with the same characteristics. A survey with workers suggests that this result is driven by two factors: i) fear of work extraction or mistreatment by firms in back-loaded contracts, and ii) the preference of workers to renege on contracts due to opportunity costs or family emergencies. The first factor is driven by firms knowing that workers cannot renege without incurring a loss in back-loaded contracts. In my matching experiment, I show that worker-firm separation prior to contract completion is high in daily pay (flexible) contracts, and firms extract more hours of work in steep contracts, supporting these two hypotheses.

Overall, the 54 percentage point gap between labor supply for uninsured daily-pay and steep contracts can be attributed as follows: i) Liquidity constraints – 12.2 ppt, ii) Wage theft concerns – 15.1 ppt, and iii) Demand for flexibility to break contracts – 26.7 ppt.

Table 3: Wage Theft concerns, Liquidity constraints and demand for flexibility

	Wage Theft Concerns			Liquidity constraints			Demand for Flexibility		
Smooth insured vs uninsured	0.151***	0.167***	0.134***						
	(0.033)	(0.043)	(0.049)						
Smooth vs Steep (Insured)				0.122***	0.048	0.221***			
				(0.033)	(0.043)	(0.046)			
Daily insured vs Smooth insured							0.340***	0.337***	0.351***
							(0.035)	(0.047)	(0.050)
Observations	973	549	420	964	540	424	645	328	316
Control group mean	0.40	0.39	0.41	0.42	0.50	0.32	0.55	0.55	0.54
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Complete	3 days	7 days	Complete	3 days	7 days	Complete	3 days	7 days

The dependent variable *take-up* is a binary variable which captures whether the worker was willing to accept the contract offered. I use fixed effects for labor stand, and control for respondent age, education, and half hour of survey time. Each respondent accounts for 2 observations, except for the first 300 observations. Standard errors are clustered at the individual level. * p < 0.10, ** p <0.05, *** p<0.01.

Interpreting rejection of payment structure as unemployment? In our experiment, all job offers are made at the same daily wage, with the only variation being the payment structure of the contract. The randomization of job offers ensures that workers receiving each offer are, on average, comparable, and thus should have similar reservation wages for the same job. When a worker rejects a back-loaded job offer, it suggests that the effective reservation wage for such jobs is higher, meaning that rejection should not necessarily be interpreted as unemployment. However, we observe that acceptance of the same job increases when insurance is provided, indicating that greater trust between firms and workers could lead to higher employment levels. While our results do not directly measure unemployment, they suggest that reducing the frictions highlighted in our study could ultimately increase employment.

Rejection rates in equilibrium The job offering procedure we adopt is designed to replicate how real firms offer jobs in the spot market, but there are key differences. First, firms typically make one job offer at a time, whereas in our sample, the majority of workers receive two offers. Second, at the spot market, firms are often surrounded by multiple workers, making the negotiation process more complex. For example, an offer rejected by one worker might eventually be accepted by another (as detailed in Varun (2024)). In contrast, we ensure that workers receive job offers in isolation. To assess whether these procedural differences affect the interpretation of our results, we compare rejection rates in our experiment with rejection rates from equilibrium negotiations in real markets. In our experiment, 47% of the 2,420 job offers we made were rejected, though this rate is influenced by the varying sample sizes for different contract types. In Varun (2024), real-time data from firm-worker negotiations show that 18% of jobs (N=669) result in no agreement. Given the nature of the negotiation process, a firm might make offers to multiple workers before reaching an agreement or no agreement. If we assume that firms make an average of 1.5 offers per job, the overall rejection rate would be 45%, closely matching the 47% rejection rate observed in our experiment. Thus, despite important differences in the job offering procedure, the rejection rates in our experiment are comparable to those observed when firms make offers directly, suggesting that our experimental findings are reflective of real-world outcomes.

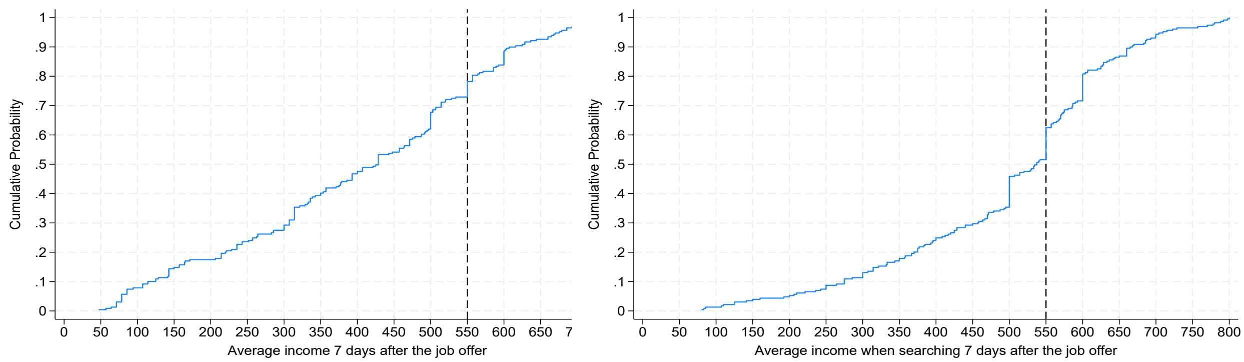
Workers forego significant earnings in rejecting jobs The results so far indicate that wage theft concerns, liquidity constraints, and the demand for flexibility play a significant role in workers' decisions to accept jobs with different payment structures. The job offers are made at the prevailing wage, suggesting that workers forego substantial earnings due to these frictions. However, it is possible that workers may receive better offers if they continue seeking work at the stand or through other opportunities.

To test this hypothesis, I collected data on worker earnings seven days after the job offer was made. This data was primarily collected by calling the workers. Since many workers did not have cell phones, we were able to reach only a sub-sample of workers (N=521, which is approximately 38% of my sample).[55]

Figure 9 shows the cdf of the earnings of workers who rejected the job offer. Approximately 72% of workers who rejected the offer ended up earning less per day (over a period of seven days) than what they would have earned if they had accepted the job offer. The workers who rejected the job offers earn 27% less income per average than they were offered in the job. The losses are primarily driven by workers who rejected back-loaded contracts, with a 33% loss for back-loaded contracts and a 3% loss for rejecting daily pay contracts. Workers who rejected insured back-loaded contracts earned 25.4% less income than what they were originally offered. Not all workers in the sample were searching for work every day during the seven days after I made the job offer. Therefore, I calculate the average search income—the average income over the days the worker was actively searching for work. Using this measure, approximately 52% of workers earned less income than they would have if they had accepted the job offer.

[55] Workers who had a cell phone reported earning 3% more income over the four days prior to the job offer, so the mean from the post-offer survey is likely to be an underestimate.

Figure 9: Earnings of workers who rejected job offers



(a) Average earnings

(b) Average earnings when searching

Notes: I calculate average income as the mean over total earnings over the 7 day period after the day of the job offer. The figure restricts the sample to workers who rejected any one of the two job offers and who I were able to survey. After winsorizing at 1% the total observations are 229. This is approximately 27.6% of the sample which rejected the job offer. The black line indicates the daily wage which was offered in the experiment. This data was collected either on phone or through in person meeting with the worker at the labor stand. In some cases the earnings were recorded for 3 days instead of 7 days. In such cases, I calculate average earnings for the 3 day period.

Robustness Checks and Randomization balance The results I have shown till now are robust to including additional covariates (see Appendix E.2), controlling for covariates selected by post-double selection Lasso method suggested by Belloni et al. (2014) (see Appendix E.1) and including surveyor fixed effects (see Appendix E.2.2). There is a possibility that workers do not trust that the field team would fulfill the insurance treatment. To account for that possibility, I ask workers the reason for denying the job offer. If they respond that they do not trust the survey team, then I assume that they would have taken up the insurance treatment arm if they trusted us. I test the predictions using this measure of take-up and find that the results are robust to this analysis (see Appendix E.2.1).

In Appendix Figure B-5, I examine the correlation between worker characteristics and their acceptance of daily-pay and back-loaded contracts. Workers with longer travel times are slightly less likely to accept back-loaded contracts. This suggests that workers coming from further away might avoid back-loaded jobs because even a minor future shock could prevent them from working on any given day, resulting in lost wages. The uptake of back-loaded contracts also declines slightly as workers' earnings over the previous four days increase.

Appendix Table C-2 shows the p-value for difference in observable characteristics for a subset of the pairs of treatment cells. I have a total of 12 treatment cells in the worker side experiment. I combine long and short contracts for the same cell which gives us 6 treatment cells.[56] I show the p-values for the pairwise comparison of these 6 cells. 9 out of the 165 variables are significant at the 10% level and 2 are significant at the 5% level. This shows that the randomization worked extremely well.

[56] I do this for ease of presentation. Note that since 78% of the sample was offered one 3 day and one 7 day contract, it is highly likely that I achieve balance on observables on the length of the contract.

4.2.1 What do workers do to protect themselves against these frictions?

The results till now demonstrate that wage theft, liquidity constraints and demand for flexibility are significant frictions for workers. Workers might adopt strategies to circumvent these concerns when they are hired by firms. I look at one such strategy which involves workers preferring to work in pairs as opposed to working alone. Working in a pair has its advantages, and one of them might be that this enables the worker to put pressure on firms if they do not pay on time (or at all). There are other non-pecuniary benefits from working in pairs too. In the words of a worker at the stands: *We prefer to work with others because having someone to talk to helps keep the mind at ease. Additionally, we can support each other if a problem arises. A lone worker can be easily pressured by the contractor, but if the contractor refuses to pay, he might be more hesitant to do so when dealing with two people rather than just one.*

To test for this strategy, I randomly offered workers three day steep contracts in pair or alone. In the pair offer, I told the worker that I would hire them along with one more worker (on the same contract) from the labor stand. This other worker was not necessarily going to be someone they knew. Each worker was offered just one contract. The rest of the randomization process was similar to the main experiment.[57] Table 4 shows the results from a regression of take-up on whether the offer was to work as a pair or alone. Take-up of steep contracts in pair is 37.5% higher than when offered alone. This provides suggestive evidence that workers choose to work and search in pairs to overcome concerns about wage theft.

Table 4: Take-up of steep contracts in pair vs alone

	Take-up	
Paired contract	0.151*	0.166*
	(0.085)	(0.084)
Observations	150	150
Mean for contracts in which offer is made to a single worker	0.39	0.39
Fixed Effect	No	Yes

The dependent variable *take-up* is variable which captures whether the worker accepts to work on a contract. The independent variable is whether the offer was in pair or alone. I use fixed effects for labor stand and control for age, education and half hour of survey time. Robust standard errors are in parenthesis. * p < 0.10, ** p <0.05, *** p<0.01.

5 Firm Side Experiment

Informal firms are often concerned that a worker may not be trustworthy and could fail to return to the site after being paid for a day's work. As shown in Table 2, this can be costly for the firm, as search costs are high. Firms in our setting are typically one-person operations (besides the workers),

[57]This experiment was conducted in labor stands after we had completed the main experiment there. The control mean may be higher as this experiment was conducted in last week of July 2024, where as the main experiment was done in April-June 2024.

Figure 10: Treatment Cells in Firm experiment

<table>
<tr><th>Days</th><th colspan="3">Payment Structure</th></tr>
<tr><td rowspan="3">3 / 7 days</td><td>Daily pay</td><td>Guarantor Daily Pay</td><td>Credit Daily Pay</td></tr>
<tr><td colspan="3">Smooth Back-loading</td></tr>
<tr><td colspan="3">Steep Back-loading</td></tr>
</table>

Notes: The total sample size is 349.

with minimal capital. They are generally paid only after all the work is completed or on a piecemeal basis for finished tasks. Consequently, their contracts with employers are back-loaded. Since nearly all of their expenses are tied to paying laborers and masons, firms face liquidity constraints when they must pay workers. The experiment is designed to isolate the effects of worker reneging costs and liquidity constraints.

5.1 Recruitment and Experiment design

Firm recruitment We recruited firms for the experiment using snowball sampling. We initially approached firms that were hiring workers from the labor stand and asked them to connect us with other firms. After a few rounds of referrals, we finalized the sample. For the experiment, we focused on firms that planned to hire a worker within four weeks of the baseline survey. To confirm this, the field team contacted each firm and inquired whether they would need a worker in the next month. If the firm confirmed, we sought their consent to visit them at their office or work site for a survey and contract offer.[58] After setting the appointment, two enumerators visited the firm's site to conduct the experiment. The representative of the firm we talked to was the owner. Most of the firms in our sample are one person units and only 10% firms have another person which helps the owner manage multiple work sites.

Design To accurately elicit the firm's willingness to offer a job under a particular contract, I implemented a procedure based on the **Becker-DeGroot-Marschak** mechanism. Workers were paid a wage W for each day of work, where W represented the prevailing wage in the labor market. Since workers and firms often have differing beliefs about the going wage, and negotiations over wages are common, I offered to hire workers on behalf of the firm at a daily wage of $W - 50$ INR, while the workers would still receive W INR. We covered the 50 INR difference, ensuring that neither the firm nor the worker incurred undue losses due to the experiment. Additionally, firms benefited from reduced search costs, which further increased the effective benefits provided by the experiment.

The experiment on the firm side consists of following treatment arms (shown in Figure 10):

1. **Payment structure:**

[58] When calling the firm owners, we informed them about our study and obtained verbal consent. To build trust, we also provided the location of our field office, which they were welcome to visit if desired.

- Steep back-loading: Firm had to pay 300 INR on Day 1 and the remaining payment ($3*(W-50)-300$ INR for a 3 day contract, and $7*(W-50)-300$ for a 7 day contract) being made on the last day.
- Smooth back-loading: Firm had to pay 300 INR on each day except the last day. The remaining payment was to be made on the last day.
- Daily Pay: Workers were to be paid INR $W-50$ at the end of each day.

2. **Guarantor:** Firms were told that we will provide them with the identification card of the worker to build trust. Additionally, firms were offered a compensation of 200 INR if the worker failed to turn up to the site on any day during the contract. We would also provide them with a worker to replace the absentee worker if needed. These conditions were provided to the firm in the form of a written agreement. The treatment was aimed at understanding the effects of worker separation costs on the equilibrium choice of contracts. Firms were offered this contract on the daily pay structure. The goal was to ensure that the contract relaxes concerns about worker separation but not liquidity constraints.

3. **Relaxing liquidity constraints:** In this treatment, firms were offered credit to pay the workers. Additionally, we provided them the option of paying the worker on their behalf. If they took this option the enumerator would go to the work site and pay the worker at the end of each day. This was intended to reduce the costs that firms had to spend on being at the work site at the end of each day. These can be thought of as transaction costs. Firms were expected to return the credit back within two weeks after the contract period. This treatment arm was cross-randomized with daily pay and smooth payment structures. The credit was provided on the payment structure of the contract.

4. **Length of contract:** Firms were offered contracts of two lengths, 7 days and 3 days. This arm was cross-randomized with the three above.

The total payment that the firm has to make (which is paid to the worker) in all cells is the same. For the analysis, we restrict ourselves to these 10 treatment cells.[59]

Contract implementation We made offers to the firm on the 10 different contracts and asked whether they would hire a worker for each one after the other. The order of questions was randomized. After the firm responded to all contracts, one was randomly selected, and their choice for that contract was implemented. The firms were informed about this procedure in advance. Since there

[59]We also cross-randomized credit daily pay with the guarantor treatment. A smooth contract solves the issue of worker separation by back-loading wages, but does not solve the credit constraint problem. Hence, we do not cross-randomize the guarantor and guarantor*credit arm with smooth and steep back-loading arms. Credit arm is cross-randomized with smooth contract. We restrict ourselves to the results from the 5 main treatment arms for the sake of brevity. After cross-randomization, we have 14 treatment cells, two for each length. The list of contracts is: i) Daily Pay ii) Daily Pay Credit iii) Daily pay Guarantor iv) Daily Pay Credit + Guarantor v) Smooth vi) Smooth Credit vii) Steep. Here the first word (Daily, Smooth, Steep) describes the payment structure, and the second word (Credit, Guarantor) describes the treatment offered on the contract.

was a positive probability of any stated choice being implemented, the mechanism was incentive-compatible.

If the firm agreed to hire a worker on the randomly chosen contract, we promised to recruit one for that contract. After the experiment, surveyors asked the firms to provide a date when the worker would be needed. If firms were unsure about the date, we asked them to call us when the demand arose.[60] After the experiment concluded, we offered to recruit more than one workers for firms if required. These workers were recruited based on the contracts the firm had accepted in the choice experiment, including those not randomly chosen at the end of the elicitation procedure. Since firms were unaware of the option to hire multiple workers before responding to the experiment, their choices were not influenced by this possibility.

5.2 Results from firm side experiment

Equation 5.1 is the specification that I estimate. T_{kj} is an indicator for firm j and treatment k where k takes 5 values and represents the 5 treatment arms. I combine responses for 7 day and 3 day contracts under one category, and use fixed effect for length in the estimation. I also use fixed effects for order of the question, and whether the respondent (the owner of the firm) is a former mason, and control for their education, number of sites the firm is operating and size of the firm (number of workers in the firm). I use the specification to test the predictions from the model.

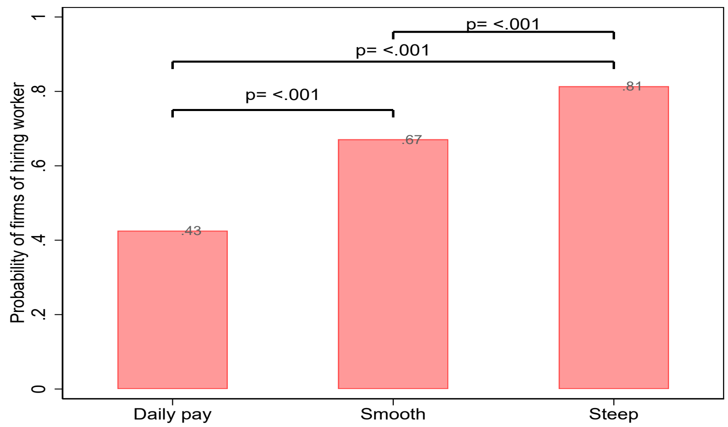
$$Y_{jk} = \alpha + \Sigma_k \beta_k T_{kj} + X_j + \mu_j + \epsilon_j \tag{5.1}$$

Prediction F.1 states that the probability of hiring a worker increases with the steepness of back-loading. Figure 11 shows the results of testing this prediction using specification 5.1. Firms are 89% more likely (38 percentage points) to be willing to hire a worker on a steep back-loaded contract than on a daily pay contract, for which the take-up rate is 43%. The acceptance rate for smooth contracts, which reduce worker reneging, is 67%, 24 percentage points higher than for daily pay. Thus 63% of the gap between demand for daily and steep contracts can be attributed to higher costs from worker reneging in daily pay contracts. While reneging rates may vary between smooth and steep contracts, they are likely to be similar as both contracts withhold some wages and hence most of the 14 percentage point gap between daily pay and steep contracts can be attributed to liquidity constraints that the former imposes on the firm.

While the steep contract relaxes some credit constraints, it does not fully alleviate these constraints for all firms, as some are compensated by their employers at intervals longer than a week. The credit treatment arm fully alleviates these credit constraints and reduces transaction costs by saving firms the need to be present at the site at the end of the day to pay workers. Figure 12 tests **Prediction F.2**. Firms are 106% more likely to accept a daily credit contract, which provides credit to pay workers, compared to a daily pay contract that does not offer such credit. The acceptance rate of credit contracts is 8 percentage points higher than that of steep contracts (p-value < 0.001).

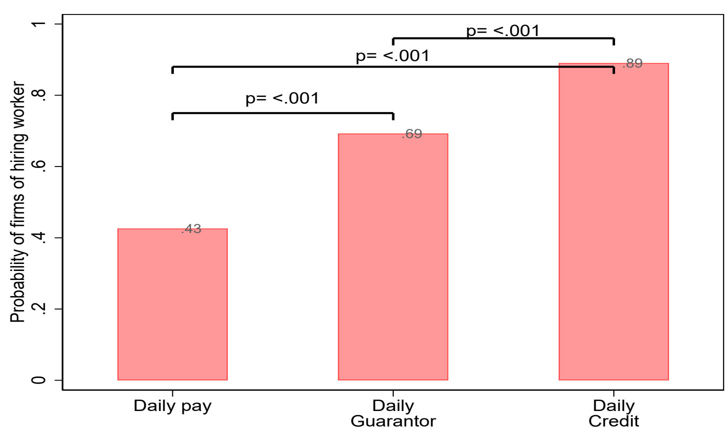
[60]The demand for workers in construction is volatile. As labor costs are the largest portion of firms' expenses, hiring workers at the right time is crucial to prevent losses.

Figure 11: Probability of hiring and steepness of back-loading



Notes: The figure shows coefficients estimated from Eq: 5.1. The total sample consists of 349 firms. I control for education of the owner, number of sites the firm is operating and size of the firm. I use fixed effects for order of the question, whether the respondent (the owner of the firm) is a former mason and for contract length. Standard errors are clustered at the firm level. p-values are shown for different pairs for a two sided test.

Figure 12: Probability of hiring on daily pay vs credit vs guarantor



Notes: The figure shows coefficients estimated from Eq: 5.1. The total sample consists of 349 firms. I control for education of the owner, number of sites the firm is operating and size of the firm. I use fixed effects for order of the question, whether the respondent (the owner of the firm) is a former mason and for contract length. Standard errors are clustered at the firm level. p-values are shown for different pairs for a two sided test.

This provides evidence that the steep contract does not fully alleviate credit constraints and that transaction costs are also important for firms.

Figure 12 tests for the difference in take-up between daily pay and guarantor contracts. This comparison bears out the prediction in **Prediction F.3**. The daily guarantor contract which mimics the smooth contract by compensating them for worker separation has a similar coefficient (p-val = 0.494) to the smooth contract. Overall, these results suggest that worker separation costs and liquidity constraints are important factors for firms. The preferences of firms on payment structure are exactly the opposite of the preferences of workers.

Liquidity constraints can affect a firm's ability to pay workers on time. For example, a firm might hire a worker on a 7-day contract, expecting payment from its employers within that period. If the employer doesn't pay, the firm can't pay the worker. Workers would perceive this non-payment as wage theft. Thus, injection of credit could help firms make timely payments and reduce workers' concerns about wage theft.

While the experiment was conducted with firms who planned to hire a worker, not all firms ended up hiring a worker on a contract. In Appendix Figure B-6, B-7 I show the results for firms which ended up hiring a worker. Naturally, the acceptance rates for all contracts for these firms is higher than the overall sample.[61] However, the signs and difference in magnitudes between different treatment arms remains broadly the same. The results are robust to controlling for covariates selected by post-double selection Lasso method suggested in Belloni et al. (2014) (see Appendix E.3).

How do liquidity constraints and limited commitment affect efficiency? Our results show that the costs of worker reneging and liquidity constraints significantly influence firms' labor demand. It is possible that firms are able to find workers outside the spot market on contracts which are favorable to them, in which case the efficiency effects of these frictions are limited. To assess whether these frictions are binding constraints for firms, we conducted a separate survey with a sub-sample of 120 firms. We asked them if they had faced difficulty hiring workers for new projects in the past; 55% responded affirmatively. Moreover, 53% of firms reported that they wait for a trusted worker, someone who has worked with them before, to become available when starting a new project. These findings suggest that the frictions we highlight can lead to inefficient hiring delays and may result in underexploration by firms, which is inefficient (Chandrasekhar et al. (2020)).

5.3 Hypothetical matching rates under different contracts

In this subsection, we conduct a straightforward exercise. We use the results from our worker and firm-side experiments to determine the matches each contract can generate in equilibrium. One caveat to keep in mind before we proceed is that the firms were made offers at a daily wage which was 50 INR below the worker's offer. Therefore, their demand at the wage offered to workers is going to be lower.

[61] Note that some firms rejected all contracts as the wage at which I offered to hire workers was not acceptable to them.

Table 5: Hypothetical matching rates under different contracts

Contract	Maximum possible matches %	Binding side
No Insurance		
Daily Pay	43	Firm
Smooth	40	Worker
Steep	28	Worker
Insurance		
Daily Pay	43	Firm
Smooth	55	Worker
Steep	42	Worker
Credit to Firms	82	Worker
Guarantor for firms	69	Firm

Notes: Matching rates are determined by taking the minima over the average acceptance rates for (3 and 7 day) contract on both the firm and worker sides of the market.

To calculate the matching rates, we take the minimum over the acceptance rate of a contract on both sides of the market. Table 5 shows the results from this exercise. Within our three base contracts, the smooth insurance contract has the highest matching rate. If we include *credit* and *guarantor* contracts then daily pay credit contract has the highest matching rate.

6 Matching experiment

The firms and workers who accepted their respective contracts were matched accordingly. The details of the matching process are described in the following paragraph.

6.1 The matching process

Matching the firm with the worker Firms reported their labor demand and hiring timelines after the hiring experiment. Simultaneously, another team conducted the job offer experiment at labor stands. Given the high travel costs, both experiments were conducted simultaneously within the same city area.

When a firm communicated their demand, the field team randomly contacted eligible workers from the pool, either by phone or at the labor stand. Eligibility was determined based on the worker's contract choice, their random assignment during the experiment, and their location. In many cases, a worker was already engaged at another construction site and informed us they would be available only after their current job was completed. In such instances, we contacted the next eligible worker on the list. Due to the idiosyncratic nature of labor demand, there were cases where we did not have enough available workers in the pool. In these situations, we contacted workers who were eligible based on contract choice and location, but whose randomization initially resulted in a no-job outcome. In a few cases, workers were offered a job on the same day as the survey, provided they met the three criteria mentioned above.

An enumerator accompanied the worker to the work site on the first day, mimicking the typical practice of firms, which generally escort workers to the site on their first day.[62] Workers were provided with a consent form outlining the details of the contract, and firms were given a similar consent form. Firms were not informed whether the worker was on an insurance contract. Workers were told during the job offer in the worker experiment that they would not be insured if they deliberately shirked in the job, and this information was reiterated at the start of work. Workers were also not informed whether the firm was on a guarantor contract. After this point, our involvement in the process was minimal, and the firm and worker interacted independently, as they would have if the firm had hired the worker directly.

Post-matching An enumerator conducted a brief survey with both the firm and the worker at the end of each day of the contract, primarily over the phone. The enumerator gathered information on the number of hours the worker worked, the tasks they performed, and whether they were paid according to the contractual agreement. If the worker had not been paid, the enumerator was authorized to pay them the outstanding amount.[63] The same set of questions was asked to the firm to ensure that there was no bias in the information provided by the worker. Throughout the analysis, we cross-check for discrepancy in reporting from both the firm and worker.

If the worker stopped coming to work before the contract ended, we offered the firm compensation if the worker was on a guarantor contract. Similarly, if the worker was removed from the job before completing the contract, we provided compensation for any unpaid work they had completed.[64] If the firm reported that a worker did not show up, we followed up by contacting the worker either by phone or at the labor stand to inquire about the reasons for their absence.

The aim of the matching experiment was to understand how workers and firms behave under different contracts in equilibrium. Before the experiment began, we were uncertain whether there would be sufficient demand from firms for the available workers. Given this concern about sample size, we decided to analyze firm and worker behavior post-matching only for steep and daily pay contracts. As a result, we did not match workers and firms on smooth contracts. To address this, we upgraded any worker who had accepted a smooth contract to a daily pay contract, since the daily pay contract is strictly preferable to the smooth contract for workers. Similarly, on the firm side, we upgraded firms that accepted a smooth contract to a steep contract, as this contract is strictly preferable for firms.[65]

6.2 Summary of Matching

Table 6 shows the descriptive statistics of matching experiment for the firms and workers. Panel A shows the number of workers who were surveyed at each stage of the experiment. A total of 1360

[62] 95% of the firms we surveyed reported that they take the worker to the work site on the first day of the contract.
[63] This was done regardless of whether the worker was on an insurance contract or not.
[64] We recorded the reasons for both the removal and any instances of non-payment. An enumerator discussed the reasons regarding non-payment with both the firm and worker. They were instructed to contact the supervisor if there was any conflicting statements about who had breached the agreement.
[65] We asked both firms and workers for their consent to work on the upgraded contracts and proceeded only if they approved.

workers were made job offers, out of which 874 accepted any kind of job offer. Out of this 280 were randomly chosen by the computer to receive the job. Due to difficulties arising from idiosyncracies in demand we had to contact workers outside this pool. A total of 382 workers were contacted out of which 276 workers were allotted work. Among the 106 workers who did not take up the offer, 15% left the city and 31% found a long-term job.[66] 17 workers out of the 276 who were allotted work did not reach the work site or left the work site soon after joining work or were not given a job due to firm backing out.[67] Out of the 259 workers who completed at least one day of work, 56 were allotted work on steep contracts and 203 on contracts with daily pay. The ratio of workers in the two contracts is similar to the ratio of take-up of daily pay and steep contracts in the take-up experiment.

Panel B and D shows the details of matching for firms. Total 349 firms were surveyed, out of which 335 agreed to hire worker on at least one contract. All firms, for which the randomly drawn contract had been accepted, were contacted after the experiment to provide them workers on the contract chosen by the random draw. Firms provided us with demands as far as one month in the future. Some firms told us that they had already hired a worker, and would contact us as per their needs. Some firms were too far away from the labor stand, and workers refused to work at those sites. Due to these reasons, we were able to match a worker to 75 firms. This is 23% of the firms which had agreed to hire at least one worker. More firms were matched on daily pay contracts than credit contracts. This is because the random draw of contract had higher drawing chances for daily contract.

6.3 Results

I analyze the action of firms and workers under steep and daily pay contracts. The specification is shown in equation 6.1. Here, D_{ij} is an indicator which takes value 1 if the contract is a steep contract. X_i includes controls for the worker i, such as the time it takes the worker to reach the labor stand from their home, and μ_{ij} are fixed effects for insurance contract, length of the contract, the daily wage and the month of work.[68]

$$Y_{ij} = \alpha + \beta_m D_{ij} + X_i + \mu_{ij} + \epsilon_{ij} \tag{6.1}$$

The coefficient of interest is β_m which captures the effect of a steep contract on the outcomes of the worker/firm. I pre-registered the study at the AEA RCT registry. The outcome variables I show in Table 7 were pre-specified.

Worker Separation Table 7 shows the estimates for equation 6.1 for different outcome variables. Column 1, 2 tests Prediction WE.1 by comparing the difference in contract completion rates across steep and daily pay contracts. Column 1 shows that the probability of completion of contracts by

[66] In Appendix Table B-1 we summarize the reasons for workers forgoing job offers in detail.

[67] If the firm backed out of the contract then the workers were compensated with 60% of daily wage.

[68] The going daily wage at the labor stand increased from 500 INR to 550 INR after the start of the experiment, and hence I control for it.

Table 6: Summary statistics of Matching

Panel A: Workers	Number of workers	
Number of workers surveyed	1,378	
No of workers offered a 3 day job	1,360	
No of workers offered a 7 day job	1060	
No of workers who accepted job	874	
No of workers chosen randomly for jobs	280	
No of workers contacted for work	382	
No of workers allotted work	276	
No of workers who completed at least one day of work	259	
Panel B: Firms		
	Number of Firms	
Number of Firms surveyed	349	
Firms which agree to hire on at least one contract	335	
Firms contacted for hiring	335	
Number of firms which hired at least one worker	75	

Panel C: Summary of contracts for matched workers	Steep	Daily Pay
Total workers matched	56	203
Total workers on insurance contracts	24	83

Panel D: Summary of contracts for matched firms	Steep	Daily Pay
Credit contracts	0	80
Guarantor contracts	0	39
Daily Pay contracts	56	78

workers increases by 23.5 ppts for steep contracts from 34% for daily wage contracts. The contract completion rate in daily pay contracts is extremely low, and back-loading the contract enables the firm to increase contract completion by 69%.

In some cases, the firm breaks the contract, either because it did not like the work done by the worker or the work ended prematurely, and for such cases I assume that the worker would have completed the contract. In column 2, I exclude those observations where the firm breaks the contract. The result remains quantitatively similar. Overall, these results suggests that workers are much more likely to complete the steep contract which back-loads wages.

In Appendix Table B-2 I list the reasons for non-completion of contracts by workers. In approximately 30% cases, workers could not go to the work site because they preferred to stay at home or there was a family emergency/illness. In 25% cases, worker reneged because the contractor was allotting too much work or asking the worker to work for long hours. To verify this hypothesis with data, I plotted the correlation between excess hours worked and the probability of showing up for work the next day in Appendix Figure B-8. The results indicate that workers asked to work longer hours are less likely to come to work the following day. 10% of worker separation is accounted for by worker finding work at some other site. This provides support for the hypothesis that workers prefer to renege because either the firm extracts too much work from them or they prefer another outside option.

Working hours Next, I test Prediction FE.1 by comparing the number of hours that the worker works for under different contracts. Workers work for 0.214 hours more (p value = 0.023) in steep contracts compared to daily wage contracts, in which they work for 8.21 hours on average. The (oral) contractual agreement between firm and workers is for 8 hours of work, but firms have a tendency to ask workers to work for longer hours.[69] This is a concern which the workers raise in the preliminary survey as well. It must be noted that even in daily wage contracts, workers work more than 8 hours on average, and this is an important reason cited by the workers for breaking contracts prior to completion.

The fact that workers are more likely to complete steep contracts than daily wage contracts, while working for longer hours suggests that the structure of payments in steep contracts allows firms to reduce worker separation costs and extract more work from workers while preventing the workers from prematurely breaking the contract, as they would lose the money that the firm has held back. While it may seem that a coefficient of 0.214 is small compared to the overall working hours, it must be kept in mind that the variance in number of working hours is low, and all except two workers work for at least 7 hours. Hence, a better metric to gauge the extent of work extracted under steep contract would be to consider 8 hours as the baseline number of hours. The coefficient for hours worked using data collected from the firms is quantitatively similar to the previous result.[70]

Now, I look at the difference in extraction of excess work by firms as reported by the workers themselves. We asked workers if they felt that the firm had asked them to work for more hours than initially agreed. If they said yes, then we asked them to report the number of minutes beyond what they expected that they work for. Workers under daily payment contract report working for 0.09 more hours than expected in total.[71] 11.2% of workers on daily payment contract state that they were asked to work for more hours than initially agreed. The same figure for steep contracts is 23.3%, a jump of more than 100%. In column 4, I report estimates of equation 6.1 for excess working hours. The coefficient for steep contracts is 0.142 which is 156% of the figure for daily contract workers.

The number of hours worked might reflect the quality of the worker, with lower-quality workers needing to work longer hours than higher-quality workers. I tested for differences in worker quality using data reported by firms. Results indicate that firms rate workers on steep contracts 0.56 points lower (p-value = 0.117) on a 10-point scale of work quality. Controlling for work quality does not substantially change the coefficient or the significance of the estimates (see Appendix Table E-8).

[69] I compensated workers for the excess hours they worked. This was done two months after job completion, when the experiment was over, to ensure that there were no spillovers of this information to other workers.

[70] Result not shown in Table. The coefficient is 0.228 (p-value = 0.01).

[71] This includes workers who said that no excess work was extracted, in which case I take the number of excess hours to be zero.

Table 7: Outcomes for workers under steep vs daily contracts

	Contract completed	Contract completed (excluding firm rejections)	Hr worked	Work extracted (Hr)	Worker Rating
Steep contract	0.235***	0.264***	0.214**	0.142**	-0.576
	(0.087)	(0.090)	(0.094)	(0.066)	(0.356)
Observations	260	233	258	260	250
Daily Pay mean	0.34	0.26	8.21	0.09	6.97
Fixed Effect	Yes	Yes	Yes	Yes	Yes

The dependent variable is measured by surveying workers and firms which were matched with each other. I use fixed effects for whether the contract was insured, length of contract, daily wage offered and control for the time it takes the worker to get to the labor stand. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

There are two potential reasons why workers' ratings on steep contracts could be lower: i) Their productivity may be lower on average, or ii) they may work less efficiently under these contracts, knowing that the firm will likely ask them to work longer hours. In Appendix Table C-3, I examine whether workers vary in observable characteristics and find that they are similar on most traits. However, workers on steep contracts had higher earnings in the four days prior to the job offer, suggesting that it is unlikely their type is lower than those in daily-pay contracts. This makes the second explanation—less efficient work due to anticipated longer hours—a more plausible reason.

Non-payment on wages Out of the 260 worker-firm matches and approximately 800 workdays, there were 24 instances of non-payment by firms. 65% of these cases occurred because the firm's representative was either absent from the site at the end of the day or lacked the cash to pay the worker. In 25% of cases, firms paid less because they believed the worker had not completed the full amount of work expected. There is no statistically significant difference in non-payment across the daily pay and back-loaded contracts.

It's crucial to note that the results reflect the actions of firms and workers who opt for either steep or daily pay contracts. The agents may differ in ways that influence their initial contract choice. Consequently, the findings are shaped by two factors: the varying characteristics of workers that affect their contract selection, and how these characteristics influence their behavior under different contract types. An alternative estimator could randomize workers into different contracts and measure how workers with same characteristics act under different contracts. My estimate, as opposed to an estimate from an experiment which randomizes workers into different contracts, provides a more accurate description of what happens in equilibrium as all the workers in the random assignment mechanism would not accept the contract which they were randomized into outside controlled environment.

The results from the matching experiment, coupled with the high demand for flexible contracts, explain the coexistence of high unemployment rates, job turnover, and worker absenteeism in low wage labor markets of LMICs. Appendix Figure B-4 demonstrates the high unemployment rate at the labor stand.[72] At the same time, workers frequently renege on contracts. This pattern suggests that workers, anticipating potential shocks, enter into easily breakable contracts. When necessary, they renege on these agreements and return to the labor stand to seek new employment.

Robustness Checks I check the robustness of the results for different specifications. Results in Table 7 are robust to controlling for additional variables (see Appendix E.5), variables selected by the post-double lasso method of Belloni et al. (2014) (see Appendix E.4) and correcting p-values for multiple testing (see Appendix E-7). Providing insurance to workers might change their productivity or actions during a job. I formally test for this in Appendix Table E-9 and find that insured and uninsured workers do not differ in their actions and outcomes.

7 Conclusion

This paper examines how limited commitment and liquidity constraints affect the labor supply and demand of firms and workers in informal labor markets. Using data collected at labor stands in India, I establish a few facts about frictions arising from limited commitment and liquidity constraints for firms and workers in this setting. I incorporate these facts in a theoretical framework, demonstrating that in an environment characterized by lack of contract enforcement and search costs, and liquidity constraints, firms prefer to pay workers at the end of the contract. This approach reduces worker separation and borrowing costs. Conversely, workers facing similar issues—consumption liquidity constraints and lack of trust in firms to pay them wages—prefer daily payments.

I test these hypothesis using an experiment with firms and workers in the construction industry in Patna, India. I find that firms are 24 ppt more likely to hire workers on contracts which reduce costs of worker reneging. Partially alleviating their credit constraints increases the take-up by 14 ppt. Fully alleviating their credit constraints and transaction costs increases their take-up by 46 ppt (from 43%). Workers on the other hand, are less likely to accept back-loaded contracts. Providing them insurance against wage theft increases their take-up of jobs by 28%. Wage theft and credit concerns are paramount in their decision making, with the latter being relevant for only lengthier contracts. Workers have significant demand for flexibility to break contracts, and this is driven by the fact that firms may force them to work for longer hours in inflexible (back-loaded) contracts and that they are inhibited from utilizing their outside option in inflexible contracts.

Workers forgo significant earnings by rejecting contracts, with 72% of those who reject contracts earning less income on average over the seven days after the job offer than they would have had they accepted it. Thus, liquidity constraints, wage theft concerns and demand for flexibility result in income losses for workers. In a separate experiment, I show that workers reduce their concerns about back-loaded payments by working together in pairs.

[72]This data, collected in August–September 2023, provides insight into the average unemployment levels at these spot markets, despite not coinciding with the experiment.

Workers and firms which accept the contracts are matched with each other and I compare the actions of firms and workers in equilibrium. Workers are more likely to break daily pay contracts before completion than back-loaded contracts. Under back-loaded contracts, workers work 0.218 hours longer than daily pay contracts, as reported by both firms and workers. This is almost double the excess time (over the agreed number of working hours) compared to daily pay contracts. Even workers in daily pay contracts work for 0.21 hours more than the agreed number of working hours, and 24% of daily pay workers cite this as a reason for breaking the contract.

These results show that limited commitment and liquidity constraints significantly impact efficiency and welfare in informal labor markets, affecting the livelihoods of individuals who rely on these markets for income. They underscore the important role labor institutions can play in this context. By enforcing legal agreements and ensuring both firms and workers honor their contractual obligations, these institutions can reshape the perceptions and beliefs of both parties regarding contract commitment. While overseeing every firm-worker contract might be too costly, the labor department could deter violations by targeting repeat offenders. This approach could foster increased trust between firms and workers.[73] Digital platforms which allow for increase in trust between firms and workers through reputation based mechanisms could lead to an increase in trust. However, their adoption is inhibited by the fact that almost half the workers don't have phones and less than 10% workers have smartphones.

Descriptive evidence from my ongoing work on worker cooperatives at labor stands suggests that both workers and firms believe a cooperative that holds workers accountable and fosters collective action could enhance trust between firms and workers, ultimately improving welfare. Additionally, injecting credit into informal markets could ease the liquidity constraints firms face when paying workers. This approach can increase the matching rate in the labor market and reduce involuntary non-payment by firms due to liquidity shortages, which often fuels workers' wage theft concerns. Moreover, improving workers' access to online payment systems could benefit firms by lowering transaction costs.

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Part I

Appendix

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A Proofs

A.1 Worker side predictions

Prediction. ***W.1***: *The probability of accepting a contract of length L with same average daily wage $\tilde{\omega}$, where $\tilde{\omega} > \omega_1^{\mathcal{C}^{Sm}} = \omega_1^{\mathcal{C}^{S}} > \underline{c}$, weakly declines in the steepness of backloading, that is, $P(\mathcal{C}^{\mathcal{D}}) \geq P(\mathcal{C}^{Sm}) \geq P(\mathcal{C}^{S})$*

Proof. Let assertion 1 be $\mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{\mathcal{D}}, 0)] \geq \mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{Sm}, 0)] \geq \mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{\mathcal{S}}, 0)]$. If assertion 1 is true then W.1 is true. Note that assertion 1 would hold trivially if $\rho < 1$ as workers are paid the same total wage over the course of L days. Hence, we will prove the statement assuming that $\rho \to 1$.

In prediction FE.1 we will show that e_j is higher for $\mathcal{C}^{Sm}, \mathcal{C}^{\mathcal{S}}$ than $\mathcal{C}^{\mathcal{D}}$. From this it will follow that assertion 1 is true.

Even if e_j is the same across contracts and firms don't defraud workers then all workers receive same expected utility on day 1. Average level of assets under daily contracts are higher than backloaded contracts and equal between smooth and steep contracts at the end of day 1. Let's show $\mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{Sm}, 0)] \geq \mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{\mathcal{S}}, 0)]$ first. Assume that Θ and $\mathcal{A}$ are distributed independently, and $\omega_1 < 2 * \underline{c}$. Then for $L \geq 3$ some workers (those with assets close to 0) will have to borrow under $\mathcal{C}^{\mathcal{S}}$ which would imply that they have to pay costs λ_B. Hence, the value of the steep contract would be lower than for smooth contracts if $\omega_1 < 2 * \underline{c}$ and $L \geq 3$.

Now, let's show that $\mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{\mathcal{D}}, 0)] \geq \mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{Sm}, 0)]$. After day 1, the worker have higher average assets under $\mathcal{C}^{\mathcal{D}}$. If all workers were to complete the contract, and all firms were honest, then the value to the workers under $\mathcal{C}^{\mathcal{D}}$ and $\mathcal{C}^{Sm}$ would be the same. But workers have an option to renege after each day 1, and the value of that option is higher for some workers under $\mathcal{C}^{\mathcal{D}}$ than $\mathcal{C}^{Sm}$ as they have higher assets on average which will provide them value (scaled by ϕ) at the end of period L. Hence, $\mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{\mathcal{D}}, 0)] \geq \mathbb{E}[V((\theta_i, A_{i0}), \mathcal{C}^{Sm}, 0)]$

□

Prediction. ***W.2***: *If q, the worker's ex-ante belief that a firm is honest, increases, then probability of accepting a contract (keeping L and $\tilde{\omega}$ the same) increases, that is, $P(j_{q1}) \geq P(j_{q2})$, where $q_1 > q_2$.*

Proof. Note that in this statement we change q only for offered contracts and not for the spot market. After that the result is straightforward to see as the value of the contract $V(j_{q_g})$ increases as expected wage increases and therefore probability of it being accepted increases. □

Prediction. ***W.2.1***: *For a smooth contract, providing insurance, that is shifting q to 1, increases the take-up.*

Proof. This follows from W.2 □

Prediction. ***W.3***: *If $q = 1$, that is workers don't have concerns about wage theft, workers are more likely to accept smooth contracts compared to steep contracts due to liquidity constraints.*

Proof. For any asset distribution with support $[0, K]$ and $2 * \underline{c} \geq \omega_1$, the constraint is likely to bind for some workers in steep contracts with insurance, and won't bind for smooth insured contracts. Hence, take-up is going to be higher for smooth insured contracts compared to steep insured contracts. □

Prediction. ***W.4***: *Workers are more likely to accept daily pay insured contracts than smooth insured contracts, due to a demand for flexibility to break contracts.*

Proof. As both contracts are insured, $q = 1$ and as both contracts pay at least $\underline{c}$ everyday there are no borrowing costs. The predictions requires us to show that despite this the value of the worker under daily pay insured contract is higher than smooth insured. Our argument is similar to proof for W.1. At the end of day 1, workers have higher average assets under daily pay contracts. The future period opportunities at the spot market or at home follow a similar trajectory for all contracts. For each contract, the utility of workers is the upper envelope of $V_{ij}^{t+1}(A_{i1})$ or $V_{ir}^{t+1}(A_{i1})$, both of which are increasing in A_{i1}, with the latter increasing strictly in assets. Hence, a convex combination of the two is increasing strictly in assets as well.

Given the error structure that we have assumed probability of takeup increases in the value of the future and hence probability of take-up increases as well.

□

Prediction. ***W.5***: *High type workers are less likely to accept a contract j, that is, $P(j|\theta_1) \leq P(j|\theta_2), \forall \theta_1 > \theta_2$.*

Proof. The value of the outside option is higher for high type workers as their probability of finding work is higher in the spot market. The probability of accepting a contract is inversely proportional to the value of the outside option, and hence probability of acceptance is lower for high type workers. □

Prediction. ***WE.1***: *In equilibrium, workers renege at a higher rate in daily payment contracts (C^D) than steep contracts (C^S) with same length L and average daily wage $\tilde{\omega}$.*

Proof. This follows from an argument similar to proof for W.4

Note that the probability of reneging at end of day 1 is directly proportional to value of reneging which is given by $V_{ir}^{t+1}(A_{i1})$, which increases strictly in A_{i1}. As A_{i1} is higher under C^D probability of reneging is higher, when $e_d = e_s = 0$. As e_d, e_s move away from 0, r_d, r_s increase at an increasing rate. See Proof for FE.1 for the remaining argument. □

A.2 Firm side predictions

Prediction. ***F.1***: *The probability of hiring a worker on a contract of length L with same average daily wage $\tilde{\omega}$ weakly increases in the steepness of backloading, that is, $P_f(\mathcal{C}^{\mathcal{D}}) \leq P_f(\mathcal{C}^{Sm}) \leq P_f(\mathcal{C}^S)$.*

Proof. From WE.1 we know that $r_{C^D} > r_{C^S}$. For C^D firms value function is lower than C^S because of higher reneging by workers. For C^{Sm}, value functions is lower than C^S as credit constraints are more likely to bind for firms with assets below $2 * \omega_1$ and reneging is lower than C^D. The result follows. □

Prediction. ***F.2****: Providing credit to firms increases their probability of hiring workers.*

Proof. This is straightforward. Providing credit removes borrowing constraints and hence the value function takes a greater value $\forall k$. $\square$

Prediction. ***F.3****: Providing compensation to firms if worker reneges on a contract increases their probability of hiring a worker.*

Proof. This is straightforward. $\square$

Prediction. ***FE.1****: In equilibrium, firms ask workers to work for longer hours on steep contracts compared to daily contracts with same length L and average daily wage $\tilde{\omega}$.*

Proof. In 3.20, the firm's profit are increasing in e_j (holding r_j fixed). At the equilibrium the marginal increase from e_j is a decreasing function of r_j (as the future value from increase in e_j declines in r_j), and the marginal loss from worker reneging due to increase in r_j is decreasing in r_j (because costs from λ_s are higher), and r_j itself increases in e_j. The marginal loss from increase in e_j is a product of $\frac{\delta r_j}{\delta e_j}$ and the marginal loss from increase in r_j. At equilibrium marginal loss must equal marginal benefit.

$$\frac{\delta r_j}{\delta e_j} * |\frac{\delta \Pi}{\delta r_j}| = \frac{\delta \Pi}{\delta e_j} \tag{A.1}$$

where $\frac{\delta \Pi}{\delta e_j} = h(r_j)$ and $h'(r_j) < 0$; $|\frac{\delta \Pi}{\delta r_j}| = g(r_j)$, with $g'(r_j) > 0$; $\frac{\delta r_j}{\delta e_j} > 0$, $\frac{\delta^2 r_j}{\delta e_j^2} > 0$.

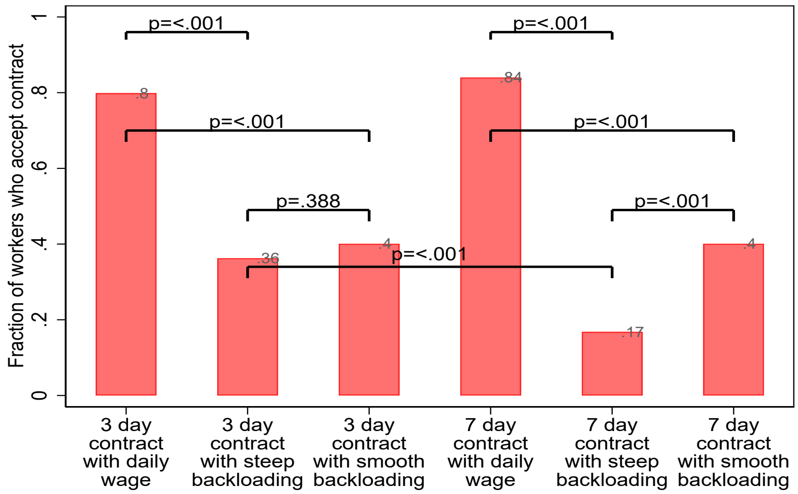
Given this, consider $e_j \to 0$ for both steep and daily pay contracts. At this value $r_d > r_s$ as value of outside option is higher under daily pay and hours worked are same. Thus the marginal benefit from increasing e_j at $e_j \to 0$ is higher for steep contract, as marginal benefit is decreasing in r_j. The value of $g(r_d) > g(r_s)$ at $e_d = e_s \to 0$. Thus, $0 < h(r_d) - g(r_d) < h(r_s) - g(r_s)$ at $e_d = e_s \to 0$. As e_d, e_s increase away from 0, r_d, r_s both increase at an increasing rate , which means that $g(r_d)$ increases at a faster rate and $h(r_d)$ decreases at a faster rate compared to $g(r_s)$ and $h(r_s)$ respectively. Hence, it must be the case that $e_d < e_s$.

Can it be the case that e_s increases to such an extent that $r_s > r_d$? Let $r_s = r*_d$, and $e_s > e*_d$. Equation A.1 must hold for both steep and daily in equilibrium. RHS is same for both, and g(.) is same as well as $r_d = r_s$. However, $e_s > e_d*$, $e*_d$ is in equilibrium and $\frac{\delta r_j}{\delta e_j}$ is increasing in e_j, which means that e_s needs to be reduced to reach equilibrium, which implies that r_s should decrease as well. Hence. $r_s < r_d$ in equilibrium. $\square$

B Additional Results

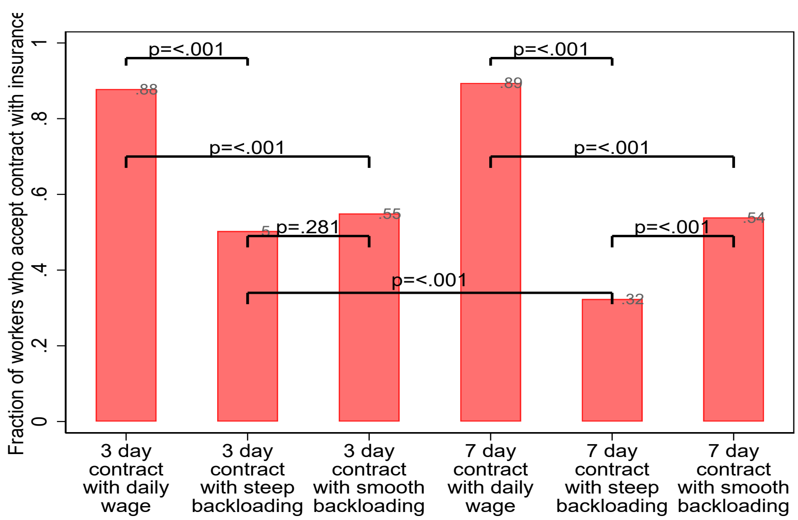
B.1 Worker side

Figure B-1: Take up of uninsured back-loaded contracts



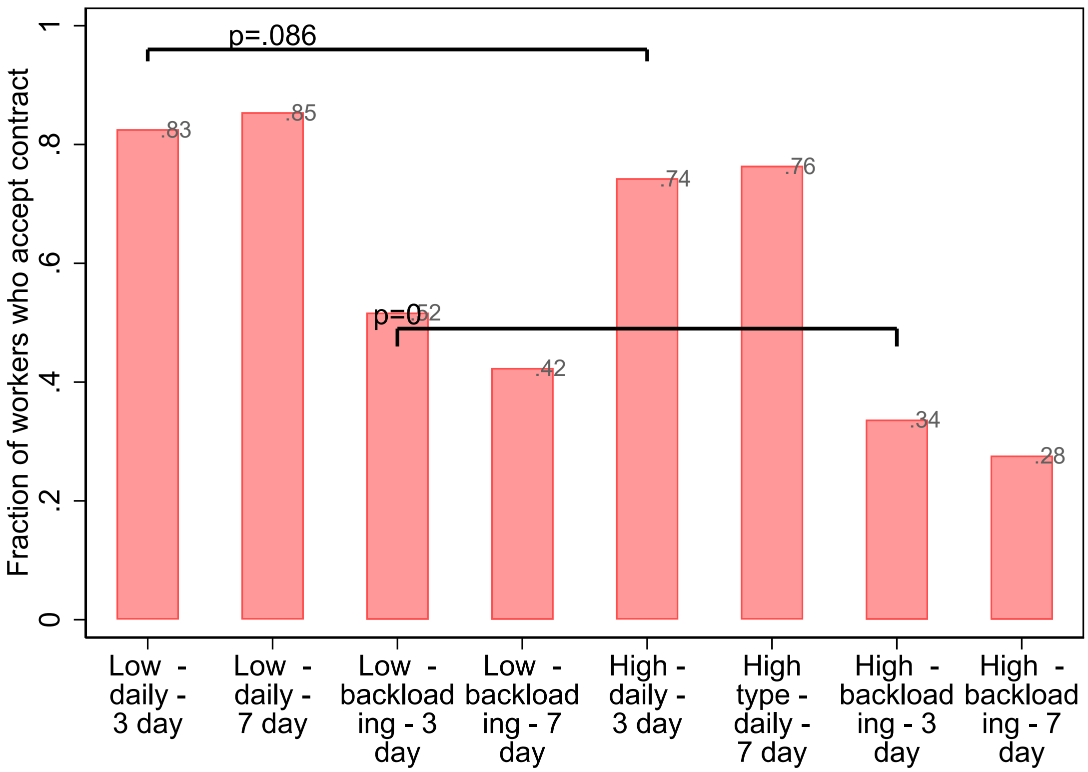
Notes: The figure shows coefficients for a regression of take up on treatment for uninsured contracts. I use fixed effects for the labor stand, and control for respondent age, education and half hour of survey. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

Figure B-2: Take up of *insured* back-loaded contracts



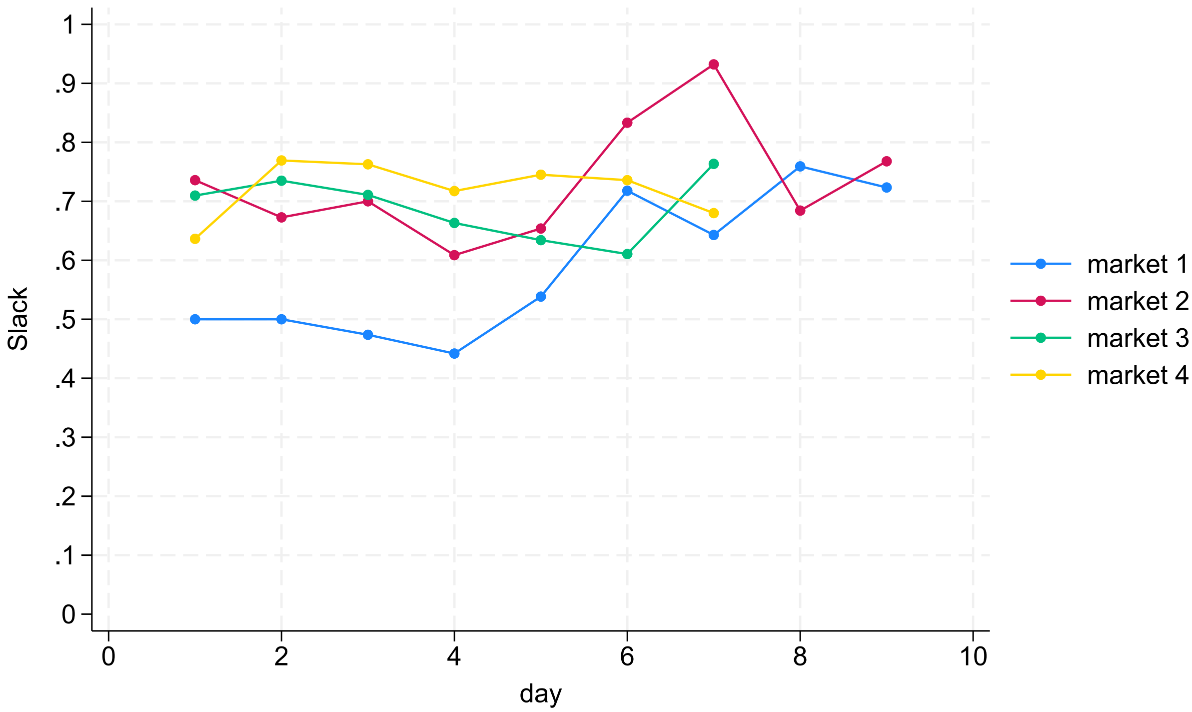
Notes: The figure shows coefficients for a regression of take up on treatment for insured contracts. I use fixed effects for the labor stand, and control for respondent age, education and half hour of survey. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

Figure B-3: Type of worker and shape of contracts



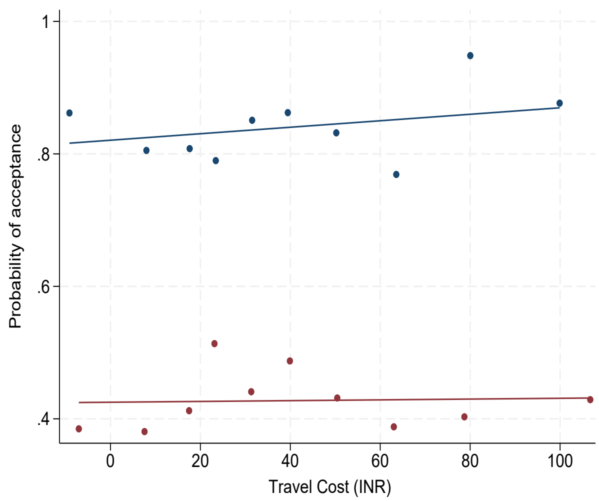
Notes: Back-loading includes both steep and smooth back-loading contracts

Figure B-4: Unemployment at the market level

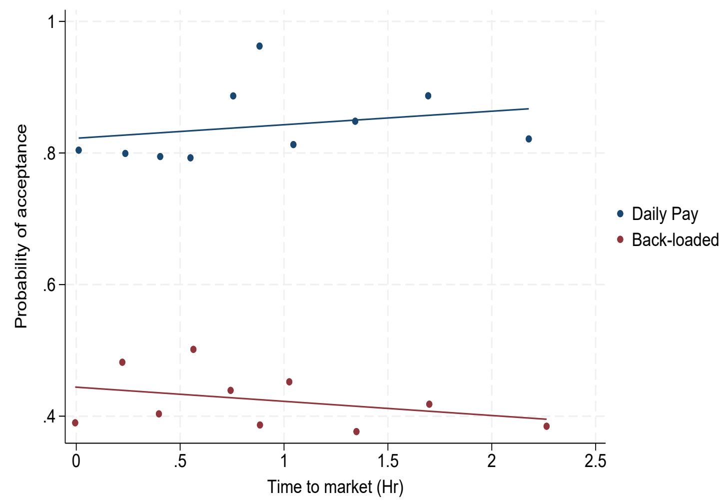


Notes: The figure shows the slack (difference between supply and number of workers who got work) at four spot markets in Patna. To plot the figure, we measure the total labor supply by collecting data for each worker who arrived at the stand for the period of our survey. We contacted each worker who visited the stand—either by phone or in-person on subsequent days—to track whether they found work. We collected data for markets 3 and 4 in the last week of July 2023, and for markets 1 and 2 in the last week of August and first week of September 2023.

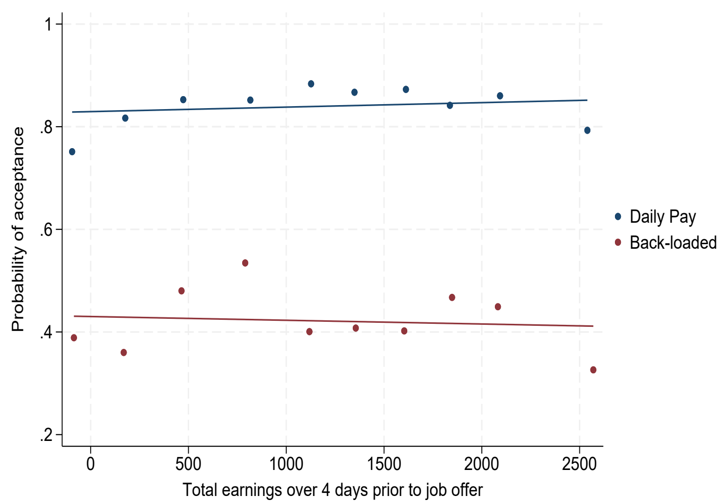
Figure B-5: Correlations between accepting offers and worker characteristics



(a) Travel Cost



(b) Travel Time

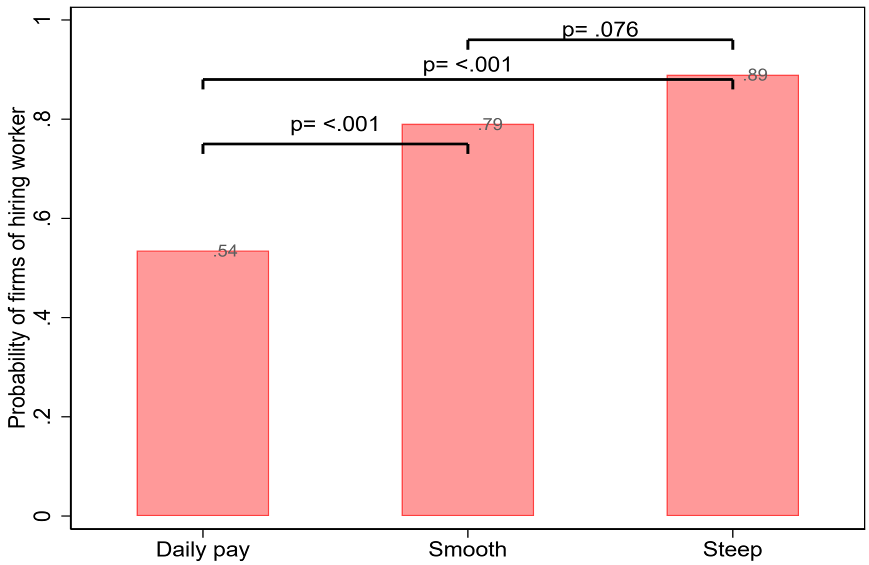


(c) Total earnings

Notes: The figure shows the correlation between accepting daily pay and back-loaded contract with worker characteristics. I control for worker age, education and hour of survey and use fixed effects for whether contract was an insurance contract and labor stand.

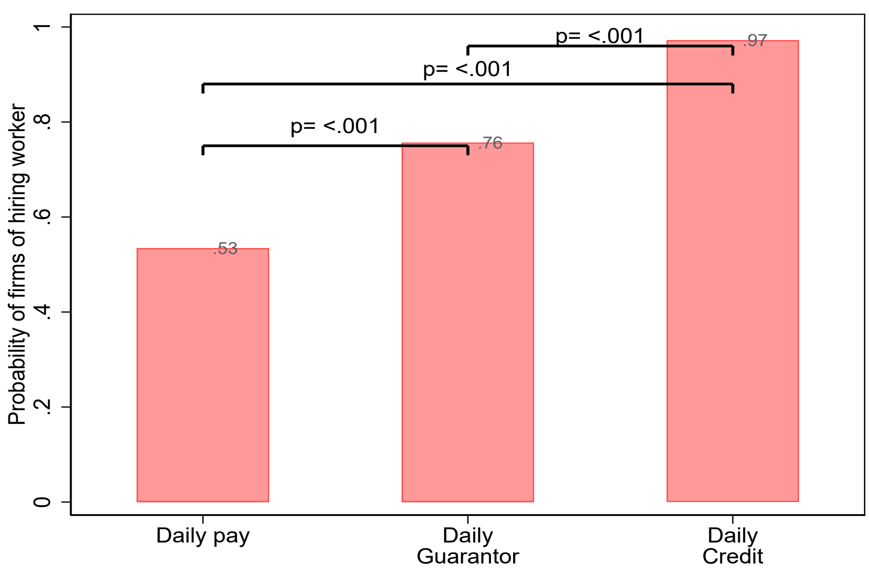
B.2 Firm side

Figure B-6: Take-up of contracts by firms



Notes: The figure shows coefficients estimated from Eq: 5.1. The total sample consists of 75 firms. I control for education of the owner, number of sites the firm is operating and size of the firm. I use fixed effects for order of the question, whether the respondent (the owner of the firm) is a former mason and for contract length. Standard errors are clustered at the firm level. p-values are shown for different pairs for a two sided test.

Figure B-7: Take-up of contracts by firms



Notes: The figure shows coefficients estimated from Eq: 5.1. The total sample consists of 75 firms. I control for education of the owner, number of sites the firm is operating and size of the firm. I use fixed effects for order of the question, whether the respondent (the owner of the firm) is a former mason and for contract length. Standard errors are clustered at the firm level. p-values are shown for different pairs for a two sided test.

B.3 Matching

Table B-1: Reasons for non-allotment of jobs

	(1) Not allotted work	
	b	pct
Went out of state	8	7.55
Went home , will come after a long time	9	8.49
Found work for a long-term	34	32.08
Refused contract: Wages are low	1	0.94
Don't want to work on steep contract	5	4.72
Don't want to work with us	18	16.98
Don't want to work as daily wage labor	11	10.38
Didn't like work	1	0.94
Not working as a labor anymore	7	6.60
could not be contacted	8	7.55
Worker unwell	4	3.77
Total	106	100.00

The table shows the break down of reasons for which workers who were contacted for job were not allotted work.

Table B-2: Reasons for Non-fulfillment of contracts

	(1) Contract not fulfilled	
	b	pct
Don't know	1	0.60
other reason	8	4.76
Stayed at home	14	8.33
Did not want to go	15	8.93
alloted a lot of work	25	14.88
Got work at other place	16	9.52
Fired from work by the Contractor	3	1.79
Site is far away	11	6.55
Family emergency/Unwell	19	11.31
Labor could not be contacted	18	10.71
Contractor was making the labor do illegal work	2	1.19
Contractor asked to come early to work	1	0.60
Contractor asked to stay late for work	17	10.12
The labor ran away in between the work	8	4.76
Contractor didn't pay	2	1.19
Contractor didn't have work	8	4.76
Total	168	100.00

The table shows the break down of reasons for which workers who started working did not fulfill the contract.

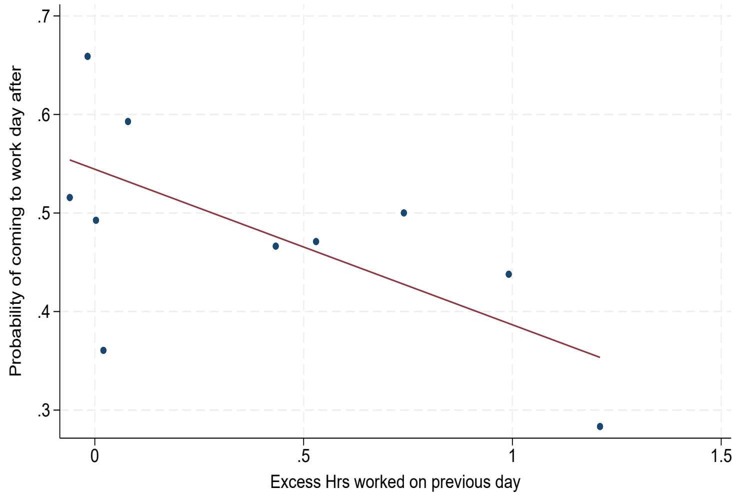


Figure B-8: Excess hours worked and worker probability of reneging

Notes: The figure shows the correlation between number of excess hours (above 8) worked on day 1 of a daily pay contract and turning up for work on the next day. I control for travel cost and use fixed effects for whether contract was an insurance contract. The p-value for the linear fit is 0.078.

C Randomization Balance

Table C-1: Balance

	Means				Pairwise differences P-values			
	Insured	Daily payment	Low type	Smooth contract	Insured - Uninsured	Daily - back-loaded	Smooth vs Steep	High vs Low
Age	32.26	32.26	32.22	32.29	0.99	0.99	0.84	0.69
Years of education	4.09	4.17	4.28	4.26	0.27	0.91	0.34	0.04
Local worker	0.39	0.36	0.38	0.40	0.86	0.11	0.17	0.04
Backward caste	0.70	0.68	0.69	0.69	0.55	0.32	0.32	0.05
Scheduled caste/tribe	0.25	0.26	0.26	0.26	0.85	0.47	0.30	0.02
Not paid atleast once (in last month)	0.20	0.16	0.19	0.17	0.22	0.24	0.97	0.15
Daily consumption cost	191.13	191.08	187.64	187.63	0.26	0.52	0.50	0.02
Total days present	2.45	2.43	2.39	2.34	0.20	0.67	0.80	0.02
Total earnings (INR)	1172.27	1166.66	1168.19	1143.07	0.81	0.74	0.54	0
Loan due	1.66	1.66	1.66	1.65	0.76	0.92	0.78	0.06
Searching for work	1.89	1.89	1.88	1.88	0.09	0.56	0.31	0.32
Time of Survey	4.64	4.63	4.60	4.62	0.97	0.77	0.19	0.13
Time to market (hrs)	0.91	0.98	0.90	0.93	0.99	0.01	0.49	0

Table C-2: Balance along main treatment cells of worker side experiment

	Pairwise differences p-values									
	U D - U SM	U D - U ST	U SM - U ST	I SM - I ST	I SM - UD	I ST - U D	I ST- U SM	I SM - U SM	I SM - U ST	I ST- U ST
Age	0.59	0.48	0.84	0.88	0.84	0.73	0.82	0.71	0.58	0.68
Years of education	0.37	0.55	0.82	0.27	0.14	0.63	0.65	0.50	0.41	0.86
Local worker	0.79	0.44	0.58	0.18	1	0.22	0.29	0.77	0.41	0.68
Backward caste	0.89	0.32	0.23	0.76	0.99	0.78	0.65	0.88	0.29	0.44
Scheduled caste/tribe	0.90	0.29	0.21	0.81	0.69	0.54	0.42	0.58	0.46	0.61
Not paid atleast once (in last month)	0.38	0.55	0.79	0.65	0.86	0.81	0.48	0.26	0.41	0.68
Daily consumption cost	0.74	0.62	0.40	0.80	0.35	0.48	0.70	0.52	0.16	0.23
Total days present	0.82	0.30	0.38	0.53	0.16	0.41	0.52	0.21	0.82	0.75
Total earnings (INR)	0.51	0.76	0.74	0.65	0.84	0.83	0.35	0.62	0.90	0.59
Loan due	0.89	0.67	0.55	0.37	0.79	0.57	0.64	0.66	0.85	0.31
Searching for work	0.38	0.52	0.84	0.33	0.77	0.23	0.03	0.20	0.32	0.06
Time of Survey	0.78	0.53	0.37	0.35	0.74	0.57	0.38	0.96	0.33	0.91
Time to market (hrs)	0.24	0.40	0.78	0.25	0.42	0.05	0.43	0.70	0.93	0.31

	I D - U D	I D - U SM	I D - U ST	I D - I DM	I D - I ST
Age	0.21	0.44	0.95	0.31	0.44
Years of education	0.21	0.48	0.59	0.85	0.26
Local worker	0.27	0.52	0.09	0.50	0.16
Backward caste	0.50	0.71	0.22	0.50	0.42
Scheduled caste/tribe	0.98	0.65	0.61	0.88	0.87
Not paid atleast once (in last month)	0.75	0.12	0.19	0.52	0.43
Daily consumption cost	0.95	0.52	0.74	0.39	0.48
Total days present	0.20	0.40	0.76	0.88	0.97
Total earnings (INR)	0.31	0.98	0.57	0.61	0.29
Loan due	0.93	0.95	0.38	0.56	0.89
Searching for work	0.26	0.99	0.96	0.20	0.07
Time of Survey	0.98	0.69	0.51	0.77	0.68
Time to market (hrs)	0.23	0.07	0.09	0.13	0.02

I show the p-values for a subset of the treatment cells. Overall I have 15 pairs of treatment cells. I show the difference for these pairs. Notation is as follows: I - Insurance contracts, U - Uninsured contracts, SM - Smooth contracts, ST - Steep contracts, D - Daily contracts.

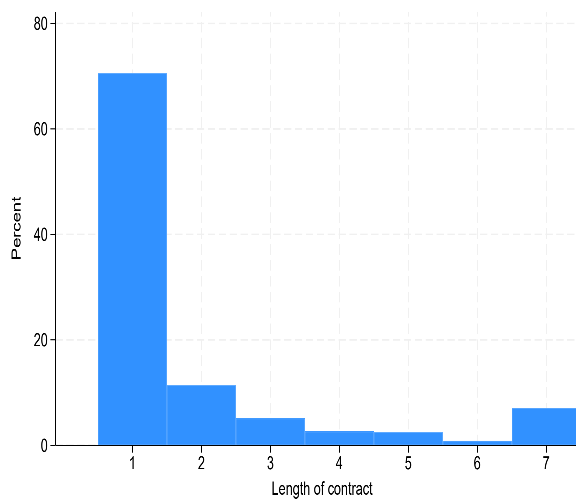
Table C-3: Balance for the matching sample

	Mean of Daily Pay	Coef	p-val
Age	31.96	-0.30	0.84
Years of education	5.17	0.08	0.92
Backward caste	0.65	0.06	0.46
Scheduled caste/tribe	0.30	0	0.97
Married	1.14	0.03	0.66
Travel Cost (INR)	47.49	-6.97	0.22
Local worker	0.33	0.10	0.19
Total earnings (INR)	1380.85	215.77	0.03
Not paid atleast once (in last month)	0.12	0.07	0.27
Daily consumption cost	192.08	-5.47	0.64
Loan due	1.57	-0.06	0.44

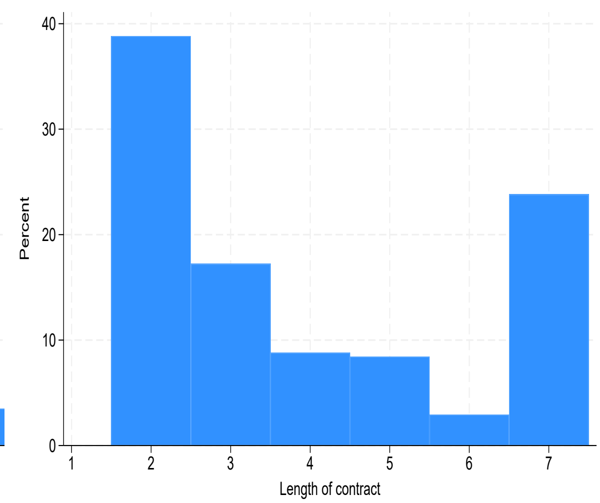
The table shows coefficients and p-value from a regression of the dependent variable on the type of contract (daily pay or steep).

D Additional Figures

Figure D-1: Length of contracts of workers at the labor stand



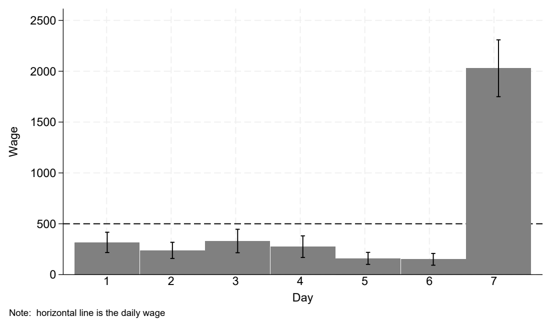
(a) All contracts



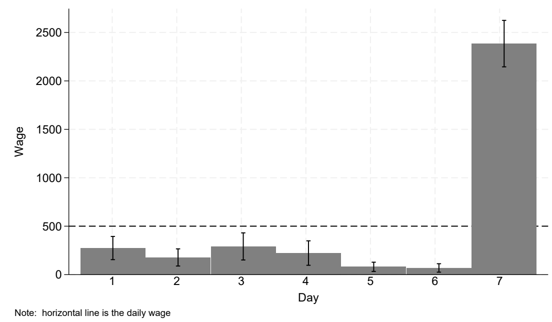
(b) All except 1 day contracts

Note: The figure shows the number of days of a job accepted by workers. These jobs were offered by firms at the labor stand. The figure is based on data (collected in August-September 2023) from a 10 day panel of all workers at four labor stands. The total number of jobs in part a) is 928. I pool all contracts of 7 or greater days into a 7 day contract.

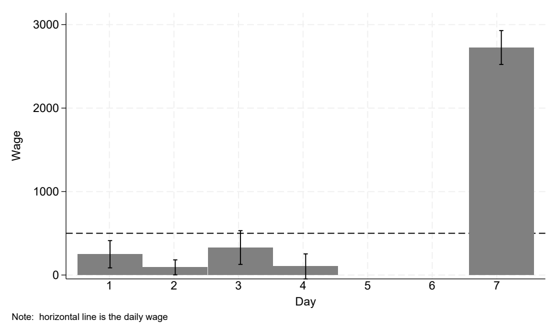
Figure D-2: Payment structure of contracts offered by firms



(a) All Firms



(b) Excluding firms which pay 500 INR daily



(c) Firms which pay on less than 3 days

Note: Firms were asked to tell us the total wages and the payment structure at which they usually hire workers for a job of 7 days. Firms first told us the total wages, their reasons for choosing that figure and then the structure. The reasons indicated that almost all firms first decided a daily wage and then multiplied it with 7 to give us the total wages. The figure shows the payment structure averaged over all firm choices for a 7 day contract. I rescale the wages offered by firms so that the total payment is INR 3500. The data was collected in May 2023.

E Robustness

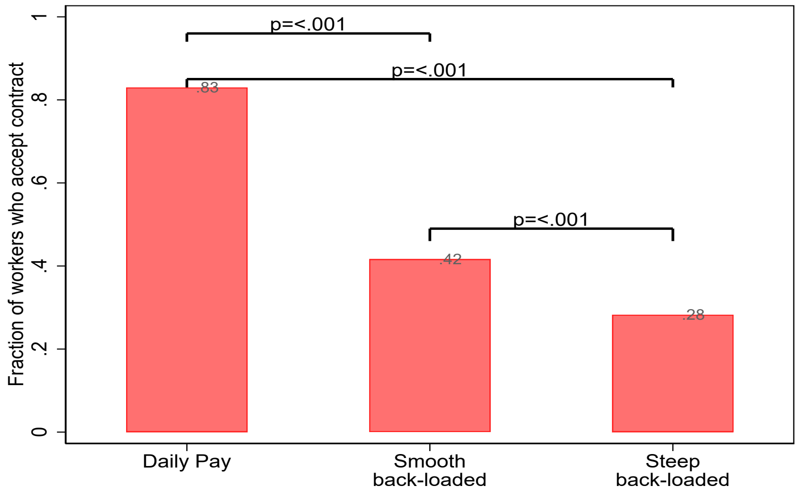
E.1 Worker Side - covariate selected using post-double selection Lasso

Table E-1: Wage Theft concerns, Liquidity constraints and demand for flexibility

	Wage Theft Concerns			Liquidity constraints			Demand for Flexibility		
Smooth insured vs uninsured	0.144***	0.163***	0.121**						
	(0.033)	(0.044)	(0.049)						
Smooth vs Steep (Insured)				0.115***	0.039	0.216***			
				(0.033)	(0.043)	(0.047)			
Daily insured vs Smooth insured							0.342***	0.337***	0.349***
							(0.034)	(0.046)	(0.046)
Observations	928	522	401	923	518	404	625	319	306
Control group mean	0.40	0.39	0.41	0.42	0.50	0.32	0.55	0.55	0.54
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Complete	3 days	7 days	Complete	3 days	7 days	Complete	3 days	7 days

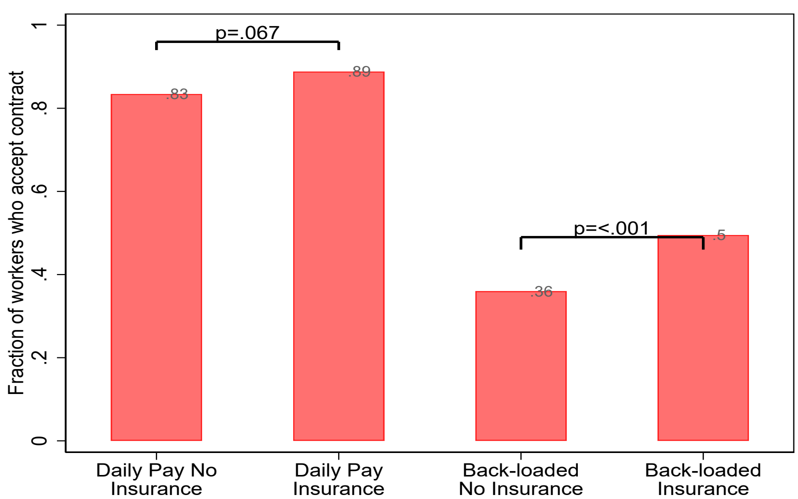
The dependent variable *take-up* is a binary variable which captures whether the worker was willing to accept the contract offered. I use fixed effects for labor stand, and control for variable selected by post-double selection Lasso method (Belloni et al. (2014)). Each respondent accounts for 2 observations, except for the first 300 observations. Standard errors are clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure E-1: Take up of uninsured daily pay vs back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for uninsured contracts. I use fixed effects for the labor stand and length of contract, and control for variable selected by post-double selection Lasso method (Belloni et al. (2014)). Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

Figure E-2: Effect of insurance on take-up of daily pay and back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for comparison between insured and uninsured contracts. I pool steep and smooth back-loaded contracts for ease of representation. I use fixed effects for the labor stand and length of contract, and control for variable selected by post-double selection Lasso method (Belloni et al. (2014)). The p-value of difference in difference test between take-up of daily pay and back-loaded contracts for uninsured vs insured contracts is 0.033. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

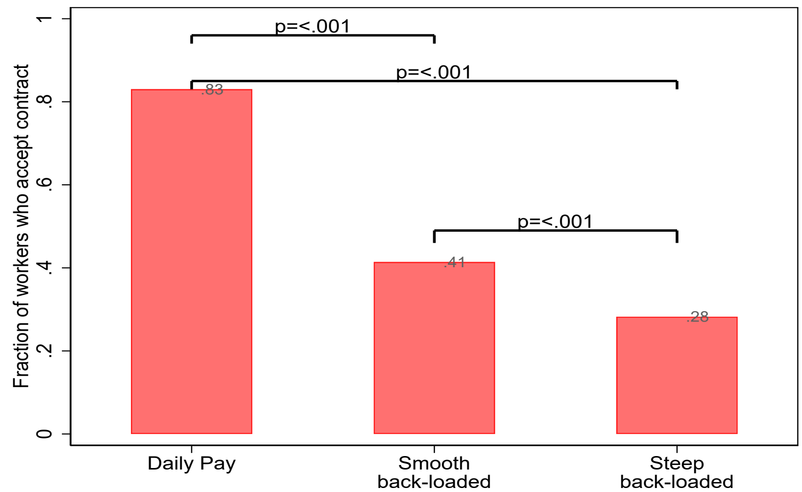
E.2 Worker Side - additional covariates

Table E-2: Wage Theft concerns, Liquidity constraints and demand for flexibility

	Wage Theft Concerns			Liquidity constraints			Demand for Flexibility		
Smooth insured vs uninsured	0.144***	0.159***	0.119**						
	(0.033)	(0.044)	(0.050)						
Smooth vs Steep (Insured)				0.118***	0.048	0.218***			
				(0.033)	(0.044)	(0.047)			
Daily insured vs Smooth insured							0.346***	0.337***	0.359***
							(0.035)	(0.046)	(0.049)
Observations	924	519	400	919	516	402	624	319	305
Control group mean	0.40	0.39	0.41	0.42	0.50	0.32	0.55	0.55	0.54
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Complete	3 days	7 days	Complete	3 days	7 days	Complete	3 days	7 days

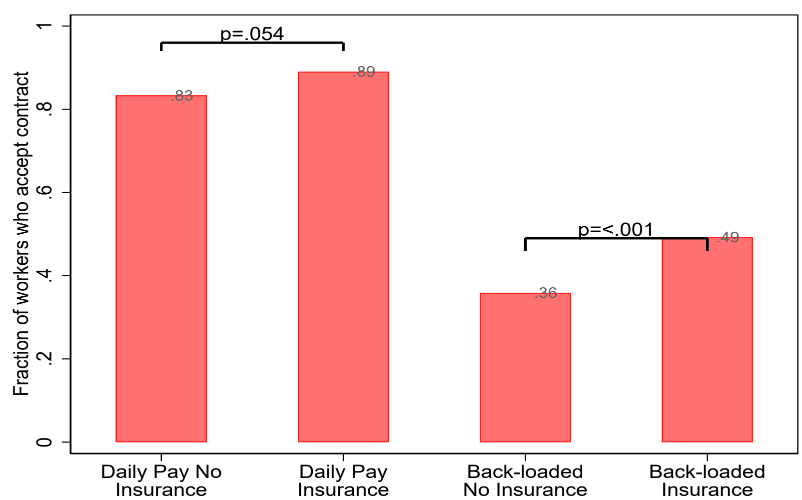
The dependent variable *take-up* is a binary variable which captures whether the worker was willing to accept the contract offered. I use fixed effects for labor stand and length of the contract, and control for offered wage; age, marital status, caste and education of the respondent; hour of survey, whether worker has a loan due, travel cost to market, no of years worked as a labor and whether they are from outside the district. Each respondent accounts for 2 observations, except for the first 300 observations. Standard errors are clustered at the individual level. * p < 0.10, ** p <0.05, *** p<0.01.

Figure E-3: Take up of uninsured daily pay vs back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for uninsured contracts. I use fixed effects for labor stand and length of the contract, and control for offered wage; age, marital status, caste and education of the respondent; hour of survey, whether worker has a loan due, travel cost to market, no of years worked as a labor and whether they are from outside the district. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

Figure E-4: Effect of insurance on take-up of daily pay and back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for comparison between insured and uninsured contracts. I pool steep and smooth back-loaded contracts for ease of representation. I use fixed effects for labor stand and length of the contract, and control for offered wage; age, marital status, caste and education of the respondent; hour of survey, whether worker has a loan due, travel cost to market, no of years worked as a labor and whether they are from outside the district. The p-value of difference in difference test between take-up of daily pay and back-loaded contracts for uninsured vs insured contracts is 0.043. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

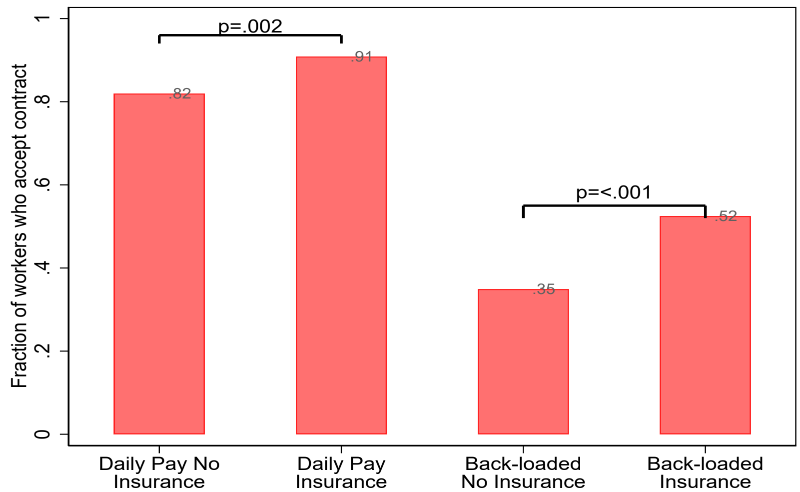
E.2.1 Estimates had the workers trusted the insurance arm completely

Table E-3: Wage Theft concerns, Liquidity constraints and demand for flexibility

	Wage Theft Concerns			Liquidity constraints			Demand for Flexibility		
Smooth insured vs uninsured	0.181***	0.192***	0.173***						
	(0.033)	(0.043)	(0.048)						
Smooth vs Steep (Insured)				0.100***	0.012	0.217***			
				(0.033)	(0.043)	(0.047)			
Daily insured vs Smooth insured							0.340***	0.336***	0.350***
							(0.033)	(0.044)	(0.046)
Observations	973	549	420	964	540	424	646	329	316
Control group mean	0.40	0.39	0.41	0.47	0.56	0.36	0.58	0.58	0.58
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Complete	3 days	7 days	Complete	3 days	7 days	Complete	3 days	7 days

The dependent variable *take-up* is a binary variable which captures whether the worker was willing to accept the contract offered. I use fixed effects for labor stand, and control for respondent age, education, and half hour of survey time. I assume that workers who deny taking up an insurance contract because they do not trust us would have taken up the job if they had trusted us and assign them a take-up of 1. Each respondent accounts for 2 observations, except for the first 300 observations. Standard errors are clustered at the individual level. * p < 0.10, ** p <0.05, *** p<0.01.

Figure E-5: Effect of insurance on take-up of daily pay and back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for comparison between insured and uninsured contracts. I pool steep and smooth back-loaded contracts for ease of representation. I use fixed effects for the labor stand and length of contract, and control for respondent age, education and half hour of survey. I assume that workers who deny taking up an insurance contract because they do not trust us would have taken up the job if they had trusted us and assign them a take-up of 1. The p-value of difference in difference test between take-up of daily pay and back-loaded contracts for uninsured vs insured contracts is 0.017. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

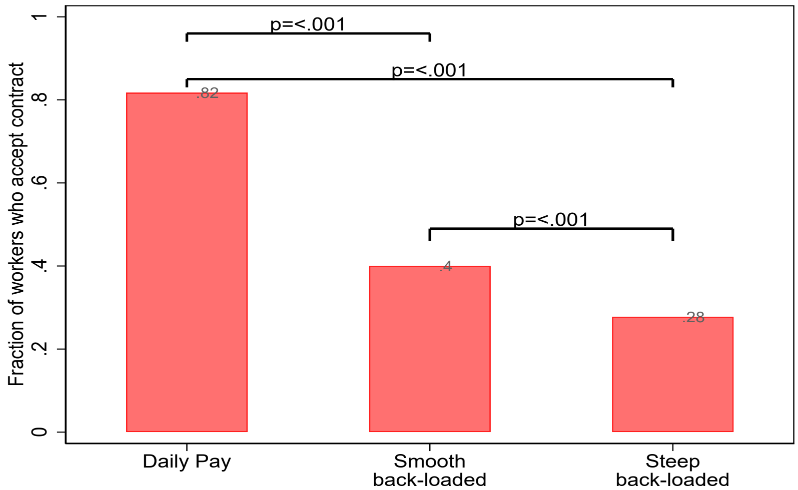
E.2.2 Robustness to including surveyor fixed effects

Table E-4: Wage Theft concerns, Liquidity constraints and demand for flexibility

	Wage Theft Concerns			Liquidity constraints			Demand for Flexibility		
Smooth insured vs uninsured	0.156***	0.169***	0.139***						
	(0.033)	(0.043)	(0.049)						
Smooth vs Steep (Insured)				0.125***	0.050	0.225***			
				(0.033)	(0.043)	(0.046)			
Daily insured vs Smooth insured							0.336***	0.329***	0.341***
							(0.036)	(0.047)	(0.051)
Observations	973	549	420	964	540	424	645	328	316
Control group mean	0.40	0.39	0.41	0.42	0.50	0.32	0.55	0.55	0.54
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Complete	3 days	7 days	Complete	3 days	7 days	Complete	3 days	7 days

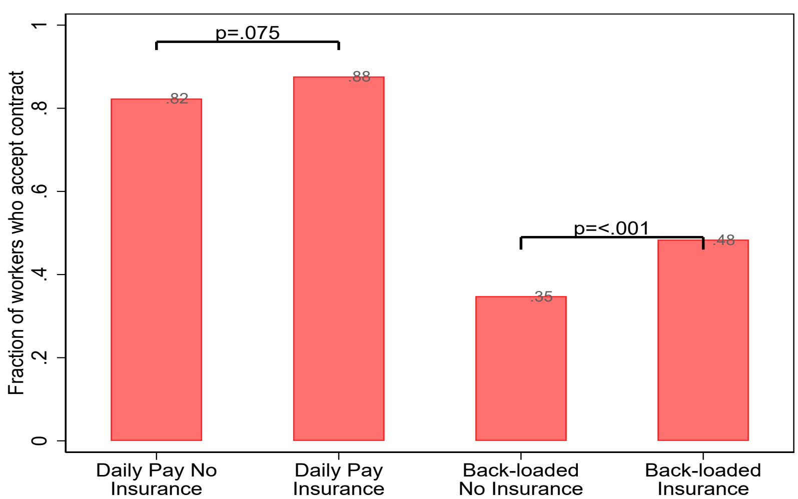
The dependent variable *take-up* is a binary variable which captures whether the worker was willing to accept the contract offered. I use fixed effects for labor stand, surveyor, and control for respondent age, education, and half hour of survey time. Each respondent accounts for 2 observations, except for the first 300 observations. Standard errors are clustered at the individual level. * p < 0.10, ** p <0.05, *** p<0.01.

Figure E-6: Take up of uninsured daily pay vs back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for uninsured contracts. I use fixed effects for the labor stand, surveyor and length of contract, and control for respondent age, education and half hour of survey. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

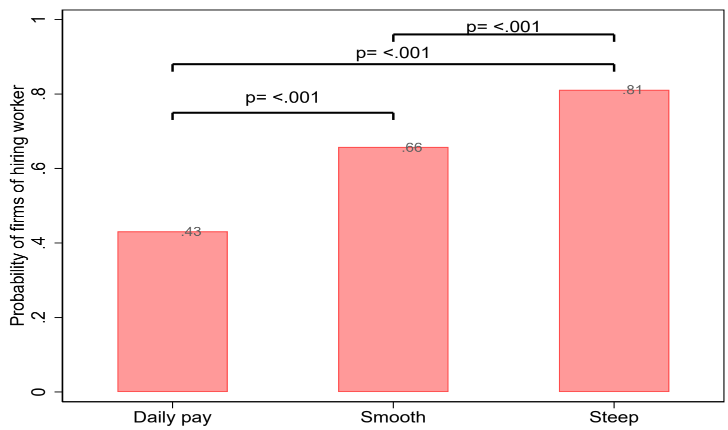
Figure E-7: Effect of insurance on take-up of daily pay and back-loaded contracts



Notes: The figure shows coefficients from regression 4.1 for comparison between insured and uninsured contracts. I pool steep and smooth back-loaded contracts for ease of representation. I use fixed effects for the labor stand, surveyor and length of contract, and control for respondent age, education and half hour of survey. The p-value of difference in difference test between take-up of daily pay and back-loaded contracts for uninsured vs insured contracts is 0.017. Each respondent (except the first 300) accounts for 2 observations (one for three day contract and one for seven day contract). Standard errors are clustered at the respondent level. p-values are shown for different pair of treatments for a two sided test.

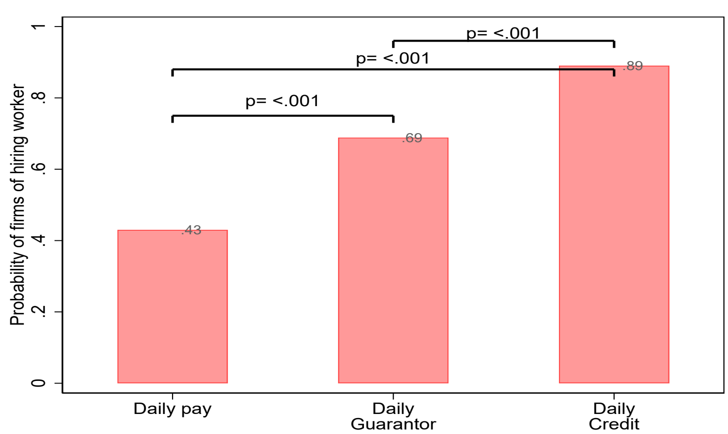
E.3 Firm Side - covariate selected using post-double selection Lasso

Figure E-8: Probability of hiring and steepness of back-loading



Notes: The figure shows coefficients estimated from Eq: 5.1. The total sample consists of 349 firms. I control for control for variables selected by post-double selection Lasso method (Belloni et al. (2014)). I use fixed effects for order of the question, whether the respondent (the owner of the firm) is a former mason and for contract length. Standard errors are clustered at the firm level. p-values are shown for different pairs for a two sided test.

Figure E-9: Probability of hiring on daily pay vs credit vs guarantor



Notes: The figure shows coefficients estimated from Eq: 5.1. The total sample consists of 349 firms. I control for control for variables selected by post-double selection Lasso method (Belloni et al. (2014)). I use fixed effects for order of the question, whether the respondent (the owner of the firm) is a former mason and for contract length. Standard errors are clustered at the firm level. p-values are shown for different pairs for a two sided test.

E.4 Matching Experiment - covariate selected using post-double selection Lasso

Table E-5: Outcomes for workers under steep vs daily contracts

	Contract completed	Contract completed (excluding firm rejections)	Hr worked	Work extracted (Hr)	Worker Rating
Steep contract	0.161*	0.196**	0.231**	0.186**	-0.677
	(0.089)	(0.087)	(0.098)	(0.071)	(0.411)
Observations	254	229	238	240	231
Control group mean	0.34	0.26	8.21	0.09	6.97
Fixed Effect	Yes	Yes	Yes	Yes	Yes

The dependent variable is measured by surveying workers and firms which were matched with each other. I use fixed effects for whether the contract was insured, length of contract, daily wage offered and control for variables selected by post-double selection Lasso method (Belloni et al. (2014)). Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

E.5 Matching Experiment - controlling for additional covariates

Table E-6: Outcomes for workers under steep vs daily contracts

	Contract completed	Contract completed (excluding firm rejections)	Hr worked	Work extracted (Hr)	Worker Rating
Steep contract	0.171*	0.213**	0.245**	0.178**	-0.540
	(0.091)	(0.088)	(0.103)	(0.068)	(0.419)
Observations	252	227	236	238	230
Control group mean	0.34	0.26	8.21	0.09	6.97
Fixed Effect	Yes	Yes	Yes	Yes	Yes

The dependent variable is measured by surveying workers and firms which were matched with each other. I use fixed effects for whether the contract was insured, length of contract, daily wage offered and control for religion, age and caste of worker, time taken to come to the labor stand, and whether worker belongs to district other than Patna. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E-7: Outcomes for workers under steep vs daily contracts with p-values adjusted for multiple testing

	Contract completed	Contract completed (excluding firm rejections)	Hr worked	Work extracted (Hr)	Worker Rating
Steep contract	0.235***	0.264***	0.214**	0.142**	-0.576
	(0.087)	(0.090)	(0.094)	(0.066)	(0.356)
Observations	260	233	258	260	250
Control group mean	0.34	0.26	8.21	0.09	6.97
Fixed Effect	Yes	Yes	Yes	Yes	Yes
p-val Bonferroni-Holm	.033		.076	.076	.111

The dependent variable is measured by surveying workers and firms which were matched with each other. I use fixed effects for whether the contract was insured, length of contract, daily wage offered and control for the time it takes the worker to get to the labor stand. Adjusted p-values use the Bonferroni-Holm correction method (Holm (1979)). Standard errors are clustered at the firm level. * p < 0.10, ** p <0.05, *** p<0.01.

Table E-8: Outcomes for workers under steep vs daily contracts after controlling for worker rating

	Contract completed	Contract completed (excluding firm rejections)	Hr worked	Work extracted (Hr)
Steep contract	0.223**	0.294***	0.152*	0.140**
	(0.085)	(0.082)	(0.081)	(0.069)
Work quality rating	0.030*	0.067***	-0.008	0.012
	(0.016)	(0.015)	(0.021)	(0.013)
Observations	250	226	249	249
Control group mean	0.34	0.26	8.21	0.09
Fixed Effect	Yes	Yes	Yes	Yes

The dependent variable is measured by surveying workers and firms which were matched with each other. I use fixed effects for whether the contract was insured, length of contract, daily wage offered and month. I control for average rating (on a scale of 1 (bad) - 10 (good)) over the contract period. This rating is given by the firm for the worker's work quality at the end of each day. Standard errors are clustered at the firm level. * p < 0.10, ** p <0.05, *** p<0.01.

Table E-9: Insurance contracts and worker outcomes

	Contract completed	Hr worked	Worker Rating	Work extracted (Hr)
Insurance contract	-0.082	0.078	0.002	0.031
	(0.060)	(0.227)	(0.039)	(0.071)
Observations	260	250	260	258
Control group mean	0.44	6.84	0.13	8.26
Fixed Effect	Yes	Yes	Yes	Yes

The dependent variable is measured by surveying workers and firms which were matched with each other. I use fixed effects for the length of contract, daily wage offered and month. Standard errors are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

F Experiment Implementation

F.1 Worker experiment

Avoiding Duplicate offers To avoid making duplicate job offers to the same worker on different days, we uniquely identified each worker using their name, age, and village name. This data was provided to the field supervisors through an online tool which was deleted after completing the survey. The enumerator was instructed to check prior to making the offer if the worker had been previously offered a job. Enumerators were also instructed to ask the worker whether they had previously been offered a job. Based on the uniqueness of name, age and village we identify zero duplicate offers in the experiment.

Avoiding Spillovers To prevent spillovers, enumerators were instructed to make job offers a short distance away from the labor stand. Job offers were made between 7:30 a.m. and 10:30 a.m. over two to four consecutive days. The number of days for continuous hiring depended on the size of the labor stand, which varied. In some cases, particularly at larger stands, the field team returned after a one-week gap. The total number of days$*$ labor stand observations are 154. We made offers at 26 labor stands and hence spent an average of 5.92 days at each stand. The average number of workers we made offers to for each stand*day is 8.83. This varied from a minimum of 5 to a maximum of 34. The average number of workers we talked to per hour is therefore between 1.66 to 10.33. Note that larger stands were allotted more enumerators. On average the labor stands have a footfall of 180 workers per day, which varies between 50 for the smallest stand to 400 for the largest stand. Thus on average, we make offers to around 5% workers each day. Many of these stands, are at intersection of roads which generates 3-4 places at each stand where workers aggregate. Given this fact and the small fraction of workers we talked to the effects of spillover should be minimal.

Survey Question The script of the job offer for a smooth insured contract of 7 days is shown below:

We want to hire a laborer for daily wage work. The work will be for 7 days. Total working time will be 8 hours every day. The work will be done with a contractor at a nearby construction site. You will be paid Rs 3850 by the contractor for 7 days; Rs 350 on the first day, Rs 350 on the second day, Rs 350 on the third day, Rs 350 on the fourth day, Rs 350 on the fifth day, Rs 350 on the sixth day and Rs 1750 on the seventh day. Total Rs 3850 for the 7 days.

You can be assured that you will get the money in full as per the contract. One of our associates will visit the site daily to ensure that the contractor pays you the agreed amount after completion of work. If you complete the work and the contractor does not pay you the amount fixed in the agreement, we will pay you the money.

All these conditions, 1) That is, when and how much payment is to be made, 2) Our payment guarantee, that is, if the contractor does not pay, we will pay you; will be given to you on a written agreement which will be signed by our organization. We will also give you the phone number and address of our organization so that if there is any problem, you can talk to us.

Instructions to Surveyor: Show the organization's card to the respondent
Would you like to work on these terms?

F.2 Firm experiment

Survey Question The script of the offer for a steep contract of 7 days is shown below:

We will provide you with a worker for 7 days for your construction work. The worker will be paid Rs. 3500 for 7 days; Rs. 300 on the first day, and Rs. 3200 on the last day. Additionally, we will pay the worker Rs. 50 at the end of each day. Payment due to the worker must be made at the end of the day. Do you want to hire the worker on these terms?

F.3 Matching experiment

Matching workers with firms who accepted the job offers Workers who accepted a job offer were provided jobs with firms who had accepted the same contract in the firm side experiment. Workers were contacted either on phone, or directly at the stand when the demand arose. All workers were provided a contact card at the end of the survey and experiment which listed the address and phone no of our field team. This allowed workers who didn't own phones but could get access to them to contact us.