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UNDERSTANDING THE IMPACT OF LOW-COST LOANS ON FORCED LABOR

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ABSTRACT

Approximately 27.5 million individuals fell victim to forced labor in 2021. The Indian construction industry is particularly vulnerable to forced labor as workers experience excessive work hours, required work on rest days, and unpaid wages. Micro-contractors (MCs), who oversee worker environments, frequently struggle with their own financial constraints due to limited access to working capital. This study investigates whether alleviating MC liquidity constraints improves labor conditions for their workers in Bengaluru and Delhi by offering randomly selected MCs access to low-cost loans. Our findings reveal this intervention does not improve working conditions overall; in fact, some outcomes slightly worsen. However, workers employed by more educated and non-migrant treatment MCs experience significantly better labor conditions, underscoring important heterogeneity among MCs. This research offers new causal insights into efforts to combat forced labor.

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A randomized controlled trials registry entry is available at https://www.socialscienceregistry.org/trials/10185

1 Introduction

Forced labor, defined as work performed involuntarily under the threat of force or coercion, is a pressing global issue. In 2021, around 27.5 million individuals were subjected to forced labor worldwide, with 17.3 million enduring privately imposed forced labor, 6.3 million in forced commercial sex labor, and 3.9 million in forced state-imposed labor (ILO, 2022).[1] This paper focuses on the 17.3 million individuals affected by privately imposed, non-sexual forced labor—the most widespread and common form. Forced labor involves various exploitative practices, including wage withholding, denial of rest days and leave, and even violence by employers. Despite many countries recognizing these practices as violations of fundamental human rights, detecting and monitoring forced labor remains challenging, particularly since much of it occurs in the unregulated informal sector. Currently, there is a lack of causal evidence on effective interventions to reduce forced labor in these contexts.

Employers of small informal firms often find themselves in precarious financial situations, grappling with issues such as delayed payments from buyers, limited access to affordable working capital, informal business practices, and challenges in recruiting and retaining workers (Nihas et al., 2013). These financial constraints can impair their ability to ensure workers' well-being and may exacerbate worker exploitation.

This paper tests whether providing low-cost loans to small firm owners can reduce forced labor. We focus on the Indian construction sector, known for its fragmentation, informality, and heavy reliance on migrant labor, which collectively contribute to the possibility of forced labor. People in forced labor are much more likely to work in manufacturing and construction relative to workers in the overall labor force (ILO, 2022). Small firm owners in the construction sector, Micro-contractors (MCs), have considerable control over key factors related to forced labor, such as workers' freedom, wage payments, and working hours. However, MCs frequently encounter liquidity issues due to delayed payments from clients who subcontract work to them. These financial difficulties hinder their ability to pay workers promptly and improve their working conditions.

To investigate whether liquidity constraints faced by MCs contribute to forced labor, we offer low-cost loans to randomly selected MCs in Delhi and Bengaluru. This intervention results in a 13 percentage point increase in intervention loan uptake (compared to a control mean take-up rate of 0 percent). In the control group at endline, 2.6 percent of MCs have taken a loan in the past month from a bank, compared to 18.4 percent in the treatment group (the 18.4 percent includes treatment loans and other bank loans). At baseline we also asked MCs if they could take out a loan if needed.

[1] Asia and the Pacific is host to more than half of the global total (15.1 million), followed by Europe and Central Asia (4.1 million), Africa (3.8 million), the Americas (3.6 million), and the Arab States (0.9 million) (ILO, 2022).

Seventy-two percent report yes to this question in the control group and 76 percent in the treatment group. This difference is not statistically significant (p-value is 0.56).

We assess changes in pre-registered indicators of forced labor risk among workers 4-10 months after the loans are disbursed. On average, workers employed by treatment MCs do not show significant improvements in forced labor indicators. In fact, conditions related to wages and working hours slightly deteriorate (by about 0.1 standard deviations). However, this average effect obscures notable differences among MC types. Educated and non-migrant MCs are able to use the loans to significantly enhance their business practices. Workers of these MCs report better outcomes, including timely and full wage payments and reduced work hours. Conversely, workers employed by less-educated and migrant MCs experienced worse conditions.

This paper makes several key contributions. First, it adds to the nascent literature on adult forced labor. Previous research has predominantly focused on child labor (Edmonds, 2008; Bargain and Boutin, 2017; Bharadwaj et al., 2020; Edmonds, 2022; Lakdawala et al., 2023; Bau et al., 2023), with some studies examining the intersection of child labor and credit constraints (Dehejia and Gatti, 2002; Lakdawala, 2018). The study by Miller et al. (2024) is the only other causal research we are aware of that attempts to reduce forced labor among adults, though it finds null effects for adults and a reduction in child labor. Our research provides new causal evidence on an intervention aimed at reducing forced labor risk among adults in India. Given the global scale of this issue, the findings from this research have significant policy implications.

Second, we also contribute to the literature on credit constraints faced by small businesses in developing countries, and the impact that loans have on business outcomes of borrowers with limited access to credit. We add to this literature by evaluating the impact of loans on previously unexplored outcomes such as forced labor risk and working conditions. Businesses in developing countries have high average returns to capital and pay high interest rates on loans (Banerjee and Duflo, 2005; De Mel et al., 2008). However, the impact of credit shocks on business outcomes, such as profits, income, consumption and the use of labor, have been found to be modest (Banerjee et al., 2015; Cai et al., 2021). Recent studies have identified significant heterogeneity in treatment effects of loans along multiple dimensions (Angelucci et al., 2015; Crépon et al., 2015, 2024; Bryan et al., 2021). Meager (2019) shows that while the impact of microcredit is negligible for business owners with no prior work experience, more experienced entrepreneurs have significantly larger beneficial effects from being offered a loan. Banerjee et al. (2019) similarly identify “gung-ho entrepreneurs” who start businesses in the absence of low-cost loans as the biggest beneficiaries of a microcredit program. We contribute to the literature on the heterogeneous effects of low-cost credit by identifying two dimensions along which our MCs are able to make use of the increased liquidity to improve working conditions for their labor: education and whether they themselves are migrants. In doing so, we add to the evidence that human capital constraints can mitigate the potential benefits for entrepreneurs with access to loans (Berge et al., 2015; Fiala, 2018; Karlan and Valdivia, 2011).

Lastly, this study offers a rigorous assessment of forced labor prevalence. Prior estimates have been derived from nonprofit organizations (ILO, 2022; Walk Free, 2023) and a limited number of research studies (Mak et al., 2017; Santhya et al., 2022; Two Six Technologies, 2021). These figures vary widely due to differing methodologies and standards, with global prevalence rates estimated at around 1 percent, and specific country estimates ranging from 30 to 73 percent in places like India and Nepal. Our analysis employs a comprehensive survey tool that assesses 24 indicators of forced labor, as defined by the ILO, among a population of workers of representative MCs in Delhi and Bengaluru. We find lower prevalence rates compared to previous reports. Specifically, while some forms of wage withholding are relatively common (10 percent of workers experience delayed payments and 18 percent are denied vacation), instances of severe exploitation—such as violence and threats to safety—are notably rare, with only 1 percent of workers facing restricted movement and threats of violence.

The rest of the paper proceeds as follows: Section 2 discusses the setting, Section 3 describes the study design, randomization and data, Section 4 discusses the results and Section 5 concludes.

2 Background and context

2.1 Prevalence of forced labor

Forced labor is defined as work that is supplied involuntarily, without free and informed consent, usually due to some form of coercion that either prevents the worker from quitting or otherwise compels them to continue working (Labour Convention, 1930; ILO, 2022). As such, forced labor can take on many forms, ranging from facing delayed payments at the relatively mild end of the spectrum to facing threats of violence and restrictions on movement at the extreme. Estimates of the prevalence of forced labor, therefore, vary considerably according to what standards are being used to measure it. The ILO estimates global slavery directly in 68 countries through Gallup World Polls, which ask respondents if they or anyone in their immediate family has been forced to work for any reason in the past five years. These national-level estimates are then weighted and combined with imputed estimates for countries which do not participate in surveys to arrive at national and global prevalence figures, which range from 0.25-2 percent of each country's total population (ILO, 2022).

Research studies in individual countries take a different approach and ask respondents direct questions on different forms of coercion (such as wage withholding or facing threats of violence), rather than asking whether the respondent has ever been forced to work. Using this approach, Mak et al. (2017) surveyed 140 Nepalese migrant workers, and found that 10 percent faced unpaid wages, 7 percent faced threats of violence, and 27 percent were forced to work overtime. Santhya et al. (2022) surveyed 236 workers in India's construction sector and 20 percent reported late pay and 96 percent reported that wages were withheld at some point. In a larger study, GFEMS (2021) surveyed over 17,000 migrant construction workers in Delhi. They found that the most commonly reported indicator of forced labor was working more hours than agreed (40 percent), working on rest days for fear of losing the job (30 percent), and not being paid the agreed upon wage (18 percent). Five percent reported facing severe threats of violence. Our study follows a similar approach. We survey respondents on 24 different indicators of coercive labor conditions they may have faced in the past three months to generate prevalence estimates. We categorize the indicators into low, medium and high severity, in line with the ILO's suggested framework, to create a picture of worker exploitation in a key sector for global labor exploitation, the construction sector.

2.2 Construction sector in India

The construction sector is characterized by labor-intensive and low-skilled work, which creates the ideal conditions for forced labor to persist. Globally, forced labor is concentrated in the construction sector, which accounts for 7 percent of the total labor force, but 16 percent of all individuals in forced labor (ILO, 2022). The construction sector in India is an important setting to study forced labor, especially since the sector is the country's second largest employer, employing 50 million and contributing 9 percent of GDP (Nihas et al., 2013). In India, forced labor in construction is a key concern for several reasons.

First, the temporary nature of construction projects and the fact that they are spatially dispersed increases the demand for casual and flexible labor arrangements (Srivastava, 2016). Keeping workers on informal contracts ensures that labor is a variable operating cost instead of a fixed cost, thus increasing flexibility and decreasing total project costs. In addition, there is tremendous pressure to keep costs low across the industry since the selection of contractors on building sites is based on bid price alone (Nihas et al., 2013; Srivastava, 2018). As a result, most construction workers are casual laborers on short-term and informal contracts, and their employers have little incentive to invest in their skills or safety (ILO, 2001; Wells, 2006; Barbosa, Filipe et al., 2017)

Second, due to the nature of the work, workers in the construction sector are more likely to be socially disadvantaged than the average worker in the population, which can exacerbate their risk for forced labor. Over a third of construction workers in India are internal migrants (Deshingkar and Akter, 2009). Migrant workers may lack information or social supports in the city where they work, and are more vulnerable to exploitation. Workers in the construction sector are also more likely to belong to a religious minority or a disadvantaged caste, which can result in elevated risks of forced labor. In fact, the majority of workers employed in construction are unskilled laborers (Santhya et al., 2022).

Third, fragmentation and informality are central to how forced labor perpetuates in the Indian construction industry (Two Six Technologies, 2021; GFEMS, 2021). Figure 1 shows the pyramidal and fragmented structure of the Indian construction sector with investor developers at the top and workers at the bottom. Investors directly invest in a few large developers, which are large, formal, corporate firms who subcontract work to large contractors who, in turn, subcontract work even further to smaller contractors (Wells, 2006; KPMG India, 2013; Srivastava, 2016; Buckley et al., 2016; LexisNexisBIS, 2016). The workers usually work for the smallest contractors in this chain, the micro-contractors (MCs), who are informal and small, but are ultimately responsible for the working conditions of workers in this sector. As a result, enforcement efforts against the large, formal developers fail because those companies have effectively hidden exploitation through diffusion; they do not have responsibility for workers on their projects because those workers are not their employees (ILO, 2001; Srivastava, 2018). Enforcement efforts at the level of the MCs fail for a variety of reasons, from lack of visibility of the informal MCs who operate on small scales, to low political will, to lack of awareness on the part of both MCs and workers about how workers can enforce their rights.

2.3 Micro-contractors and workers

Our study focuses on the pivotal role played by the micro-contractors (MCs) who are at the bottom of the supply chain in the Indian construction sector shown in Figure 1. MCs are independent subcontractors who hire small groups of workers, frequently from the same villages that they themselves originate from. MCs have significant control over workers' employment conditions, including schedules, pay, and the type of work. When exploitation occurs, it is often due to decisions made by MCs, making them key to addressing factors contributing to forced labor at the ground level.

MCs also encounter their own set of daily challenges, including delayed payments, restricted access to affordable working capital, inconsistent work orders, informal business practices, and difficulties in recruiting and retaining workers from above (Nihas et al., 2013). These challenges directly hinder MCs capacity and willingness to safeguard their workers' well-being.

Most MCs have a simple business model where they receive orders from clients – builders or other subcontractors – to execute some aspect of a construction project. They hire the labor that executes these orders, and they may also purchase some materials that are used in the construction process. For example, an MC may be hired to complete the painting of a building. He will be responsible for hiring the labor to complete the painting, and he may also spend money on paint brushes, erecting scaffolding, and other equipment used by the labor to complete the project. As such, the MC's expenses comprise only payments to labor and some other business expenses.

However, the ability of the MCs to make these payments, particularly to the labor, on time, depends on whether they are paid in a timely manner by their client.

At baseline, the greatest challenge reported by MCs in this study was delayed payments from builders (46 percent). In addition, they reported facing input constraints such as lack of workers (40 percent), lack of work orders (24 percent), and significant credit constraints. Friends and family are the most common available source of loans reported (62 percent), followed by moneylenders (22 percent), and banks (8 percent). At baseline, one-fourth of MCs reported that they would not be able to obtain a loan if they needed it. The combination of delayed payments for work performed and credit constraints might limit the willingness and ability of MCs to ensure the well-being of their workers. They delay payments to their workers either because they do not have the funds, or because they do not have the confidence to spend the cash they have in hand.

Previous studies targeted at firm behavior find that access to debt markets increases leverage and leads to less hoarding of cash (Favara et al., 2021). MCs too, could benefit from the removal of constraints to capital and liquidity, allowing them to spend more on worker conditions, increasing productivity, and reducing exploitation of their workers. If MCs are simply exploiting their workers to maximize profits in an environment with limited monitoring, additional liquidity might not affect worker outcomes. However, if MCs want to improve worker conditions but fail to do so because of a lack of liquidity, then access to working capital could lead to a decline in the incidence of forced labor among construction workers.

3 Study design

In the previous section, we established that i) MCs bear ultimate responsibility for the conditions in which their workers function, and ii) MCs face economic uncertainty and report a lack of working capital as their primary business challenge. These two characteristics inform the design of our intervention to improve worker outcomes: to offer randomly selected MCs access to low-cost loans.

3.1 Intervention details

The loan intervention was provided as part of a larger program that was targeted at MCs in the construction sector. The setting for the intervention is two large cities in India - Bengaluru and Delhi - both of which have large construction sectors. All MCs in the treatment and control groups were offered access to i) a training program on business skills and ethical worker treatment and ii) access to work orders and workers. Only treatment group MCs were informed about the possibility of receiving low-cost loans, and this information was given to them after training. Training was mandatory for all MCs in the study so take up was 100 percent. Other program components were provided upon request. Approximately 35 percent of MCs requested support with work orders and 57 percent requested help sourcing workers. However, these shares do not vary significantly by treatment status. We find no evidence that MCs who took up loans are more likely to ask for additional work orders or workers. These program components were implemented by an organization called LabourNet, which matches workers and employers in the informal sector in India.

LabourNet recruited 250 MCs into the study. To identify eligible MCs, LabourNet first compiled a list of major building and construction developers operating in both Bengaluru and Delhi. This list was based on visits to the local Chambers of Commerce as well as contacting the local association of developers. The developers were approached and asked for a list of MCs they worked with. A list of 600 MCs was compiled with 300 in each city. From this list, MCs were filtered on the basis of eligibility: they had to be at least 21 years old, have an annual income of less than Rs 10 lakhs (U$13,500), and employ at least 5-10 workers. Finally, MCs had to express interest in the program, agree to receive the training, and be willing to share data on themselves and contact details on workers with the research team. This filtering process yielded 250 MCs.

Randomly selected MCs from this groups of 250 were allocated to a loan treatment group, and were offered access to low-cost working capital line of credit by a company called Gromor Finance. Treatment MCs were given the opportunity to apply for a line of credit, and, if approved, were allowed to draw down from the 12 month credit line up to their approved credit limit. The average tenure of each drawdown was typically 90 days, though some loans were approved for 60 days. The initial approved credit limit was approximately Rs 105,000 (U$1,255) on average, varying from Rs 50,000-Rs 250,000 (U$675-3,375), which is four times the monthly salary for the average program MC during baseline. Given that the average monthly wage bill for MCs at baseline was Rs 564,000, the average loan size was 19 percent of the monthly wage bill.

These loans were offered at a monthly interest rate of 1.5 percent (18 percent annually), which is substantially lower than the alternative monthly rate of borrowing from banks, moneylenders, friends, or family. Our survey data indicates that MCs who had taken bank loans in the past month paid an average monthly interest rate of 1.5 percent as well, but bank loans are typically collateralized against assets, while the Gromor loans required no collateral. MC loans from moneylenders, which typically do not require collateral, were taken at an average monthly interest rate of 2.5 percent (30 percent annually).

Ultimately the process of accessing loans from Gromor Finance proved to be onerous and costly, particularly in terms of documentary requirements. Fifty-one percent of treatment group MCs expressed an interest in applying for a loan, but only 34 percent were able to complete the underwriting process, which required submitting the necessary documentation to Gromor. Eighteen percent had their documents rejected during the verification process and a further 8 percent of MCs withdrew during this process. Only 8 percent of treatment MCs ended up opening a credit line. We discuss loan take-up further in subsection 4.4.

Figure 2 shows the timeline of the project. We collected baseline MC data from June to December 2021, and worker baseline data from October 2021 to January 2022. Applications for lines of credit became available in November 2021. The first lines of credit were approved in March 2022, and the first drawdown was on April 28, 2022. The last MC was approved for a line of credit in July 2022. Endline MC data was collected from November 2022 to March 2023 and endline worker data from December 2022 to February 2023.

The Covid-19 pandemic sharply affected the construction sector in India, particularly during the months in 2020 when construction sites were shut down across the country. While construction contracted by 5.7 percent in 2020-21, it rebounded strongly in the next two years as restrictions were lifted and workers were vaccinated. The sector grew by 14.8 percent in 2021-22 and 10 percent in 2022-23.[2] Our study takes place during the post-pandemic period when the construction sector had rebounded (see Figure A1).

3.2 MC randomization and data collection

MCs were assigned to treatment or control groups stratified by city (Bengaluru or Delhi). Of the 250 program MCs, 90 MCs were randomized into treatment in Bengaluru and 90 in Delhi. The remaining 70 MCs were assigned to the control group (34 in Bengaluru and 36 in Delhi). MCs move from worksite to worksite to fulfil work orders from different developers. In Delhi, worksites are smaller and typically only one MC works on a single site at any given point in time. In Bengaluru, some of the larger worksites may have had multiple MCs. In all our analysis, we control for stratification by city.

Telephone surveys were conducted for all MCs, and 240 out of 250 MCs responded to the baseline survey. The other 10 MCs refused to complete the survey. Table 1 presents summary statistics on demographic characteristics and outcomes at baseline for all surveyed study MCs. Panel A presents treatment and control group means for all MCs surveyed at baseline, and shows balance across treatment and control MCs.

When re-contacting MCs for the endline survey, we collected data from 146 MCs, representing a response rate of 58 percent. A key issue we faced was that MCs were usually very busy at work and did not want to participate in a phone survey with our enumerators. Thirty-five percent of control group MCs (and 41 percent of treatment group MCs) did not respond at endline. The difference in attrition rates between the treatment and control group is not significantly different from zero (p-value = 0.41). Panel B of Table 1 presents baseline characteristics for only those 145

[2]Data is from the Indian Government's Ministry of Statistic and Programme Implementation (MOSPI) and was retrieved from `https://mospi.gov.in/data`.

MCs who were surveyed at both baseline and endline. None of the characteristics are significantly different by treatment status suggesting balance on this sub-sample of MCs.

Given that we lose 40 percent of MCs between baseline and endline, we test for differential attrition to survey response by treatment status. We regress an indicator for attrition on all MC characteristics that we collect at baseline as well as the interactions of these characteristics with treatment status. The results are provided in Table A1. Column 1 shows that baseline characteristics do not predict differential attrition by treatment status. In Column 2 we add additional interactions with the main outcomes of interest. Again, almost none of the coefficients are statistically significant. Two of the twelve interactions are statistically significant but the coefficients are quite small and go in opposite directions.

Panel C of Table 1 presents treatment and control group means for some additional demographic characteristics that were collected only at endline. Here, again, there is no significant difference by treatment and control status.

In terms of demographics, MCs in the study are between 22 and 60 years old, with an average age of 36. While 29 percent of the study MCs have not completed compulsory schooling (until grade 8), 52 percent have some high school and 18 percent have at least some college education. Most have considerable experience in construction, with almost 70 percent having worked in the sector for more than 3 years, and 59 percent for more than ten years. The median MC earns Rs 25,000 (U$338) per month as income from construction. Approximately 17 percent of MCs are Muslim, while 61 percent are from marginalized castes.

3.3 Worker data and prevalence of forced labor

The construction sector employs a large share of migrant workers and is characterized by high rates of worker attrition from MCs, as well as return migration to source villages. In our baseline survey, the median worker reported staying with an MC for eight months. Given these characteristics of the construction sector, we surveyed a cross-section of workers who were employed with the treatment and control MCs at the time of the baseline and endline surveys.

Workers were recruited through site visits by LabourNet to MC worksites for baseline and endline. Workers were offered a food packet in exchange for contact information. This information was shared with enumerators who conducted the baseline survey by telephone. All the workers we recruited had phones which is the norm these days for these types of workers. We surveyed 1,251 workers at baseline and 1,543 at endline. These 1,543 workers were surveyed across 229 MCs, of which 165 were treatment MCs and 64 were control MCs (1,136 and 407 workers, respectively, working for treatment and control MCs).

Worker summary statistics are presented in Table 2, separately by the two cross-sectional worker surveys at baseline and endline. Most workers are young males, with an average age of 30. Over

40 percent have worked in construction for less than three years. The average worker earns Rs 12,400 (U$167) per month. In our sample, MCs report paying the median skilled worker Rs 15,600 (U$210) per month and the median unskilled worker Rs 10,800 per month (U$146) (not reported in table). The median MC has a team size of 30 workers, of which 15 are permanent (not reported in table), which we take to be a proxy for skilled workers, suggesting that roughly half of the workers in our sample are skilled, and half unskilled. We do not have more accurate estimates of the share of skilled and unskilled workers in our sample since workers did not reliably self-report their level of skill.

To provide some context for the workers in our sample, we benchmark them against a nationally representative sample from the 2021-22 Periodic Labour Force Survey (PLFS), a survey conducted by India's Ministry of Statistics & Programme Implementation. We restrict PLFS data to urban construction workers of a similar age profile (construction workers who are less than 40 years old). These results are presented in Table A2 and indicate that workers in our sample are reasonably similar to workers from the nationally representative sample in terms of demographics and income. Our workers are less likely to be from a marginalized Scheduled Caste/Scheduled Tribe/Other Backward Caste (64 percent) compared to workers surveyed in the PLFS (77 percent). Their average monthly earnings of Rs 12,400 per month (U$167) is lower than the corresponding income of the Delhi subsample of the PLFS (Rs 15,000 or U$202) and similar to the Bengaluru subsample (Rs 13,000 or U$176) respectively (not shown in table).

Outcomes. The key worker outcomes we consider are indicators of forced labor outcomes that align with those used by the ILO and the Trafficking in Persons (TIP) Office of the US government. In particular, these outcomes capture the TIP Office's definition of forced labor, "Forced Labor, sometimes also referred to as labor trafficking, encompasses the range of activities involved when a person uses force, fraud, or coercion to exploit the labor or services of another person" (Department of State, United States of America, 2023). Accordingly, the worker level outcomes we measure in our surveys are measures of wage withholding, intimidation and threats by MCs, abusive working conditions and debt bondage, or the inability to quit because of an outstanding debt owed to the employer. All outcomes are pre-registered with the AEA Trial Registry (ID number AEARCTR-0010185). The outcomes were measured through survey questions proposed by the ILO to measure the prevalence of forced labor. The exact text of the questions by index are shown in Table A3. In line with recommendations from the ILO, these survey questions are selected and adapted to the local context and the target populations in the two cities of Bengaluru and Delhi (ILO, 2024).

These worker-level outcomes are summarized by treatment and control at baseline and endline in Table 3. We categorize the outcomes as constituting high risk, medium risk and low risk measures of forced labor, distinguishing between different types of coercion and how serious a threat they represent in the context of the Indian construction sector. We develop these category distinctions based on conversations with partner organizations in this project. Low risk measures include all indicators related to wage withholding. Medium risk measures include all indicators related to requiring workers to work more hours or days than previously agreed, as well as manipulation of debt owed by the worker to the MC. High risk measures include threats of violence.

The prevalence of forced labor outcomes across the sample is quite low at baseline. Most outcomes related to wage withholding and delayed payment have a prevalence rate of under 10 percent. The most prevalent forms of forced labor conditions at baseline are not being paid at double the usual rate of pay for hours worked overtime (52-57 percent), being asked to work more hours than agreed (6-7 percent), and being denied permission to go on leave as previously planned (1-3 percent). High-risk conditions of forced labor are negligible, with prevalence rates close to 0 percent of surveyed workers at baseline. While the share of workers not being paid double for overtime is relatively high, this is not a legal requirement in India for informal workers such as those in the construction sector (See the Factories Act 1948).[3]

While it is possible that workers could be under reporting instances of forced labor we took the following measures to minimize this potential problem. First, we collected data by phone and not in person, and we made sure to phone workers and speak with them at a time when they were not around their MC. We also told all workers that we would not share any of the information they provided us with their MC. Lastly we asked all workers the same questions about fellow workers who work for the same MC, in case the worker was apprehensive about answering this question for themselves. Interestingly, forced labor rates to these questions are even lower, so we do not use them in the analysis.

For the regression analysis that follows, we create indices based on these three categories of low risk, medium risk and high risk indicators of forced labor. We additionally include two more categories that capture economically meaningful aspects of worker's labor, including how much they are paid and how much they work. The components of each of the following five indices are listed in Table 3 and the questions are listed in Table A3. Each index is constructed as the standardized mean of sub-component indicators, with each index standardized separately by baseline and endline around the control group mean and standard deviation in that survey (following Kling et al. (2007)).

3.4 Empirical specification

MC specification. We first estimate the impact of being offered the loan treatment on MC outcomes. The outcomes we consider include whether the MC took a loan, and other business level

[3]The text of the Act can be retrieved here: `https://labour.gov.in/sites/default/files/factories_act_1948.pdf`.

measures such as number of workers, monthly labor bills, and other business expenses. We also investigate whether the mode of payment to MCs from their clients and from MCs to their workers changed as the treatment loan process might have formalized payment structures.

Using the cross-section of MCs who were surveyed at endline, we estimate the following model:

$$Y_{mc} = \beta_1 Treat_{mc} + \phi_c + \epsilon_{mc} \tag{1}$$

where Y_{ic} is the outcome of interest for MC m, located in city c. $Treat_{mc}$ is an indicator for whether MC m, located in city c, is randomized into the treatment group, ϕ_c includes city fixed effects, and ϵ_{mc} is a random error term. The city fixed effects are included to account for the stratified randomization. β_1 is the intent-to-treat (ITT) estimator of the impact of being offered a loan on MC-level outcomes, and is the main coefficient of interest.

We additionally validate the results with a difference-in-differences (DD) estimator that uses both baseline and endline data from MCs. We estimate the following model:

$$Y_{mct} = \beta_1 Treat_{mc} \times Endline_t + \beta_2 Treat_{mc} + \beta_3 Endline_t + \phi_c + \epsilon_{mct} \tag{2}$$

All variables are the same as above but we introduce time t (baseline or endline) and $Endline_t$ which is an indicator equal to one when data is from the endline. The coefficient of interest β_1, is the DD estimator of the impact of being offered a loan on the change in treated MC outcomes, relative to control MC outcomes, from baseline to endline.

Worker specification. We next turn to the analysis of workers. The primary outcomes are the different measures of worker risk described in section 3.3. We estimate the ITT effect of MC access to loans on worker forced labor outcomes using the endline data:

$$Y_{imc} = \beta_1 Treat_{mc} + \phi_c + \epsilon_{imc} \tag{3}$$

where Y_{imc} is outcome of interest for worker i who works for MC m, located in city c. $Treat_{mc}$ is an indicator for whether that worker's MC m, located in city c, is randomized into the treatment group, ϕ_c includes city fixed effects, and ϵ_{imc} is a random error term. β_1 is the ITT estimator of the impact of the MC being offered a loan on his worker's outcomes. Standard errors are clustered at the MC level.

We additionally present results from DD models which use the repeated cross-sectional data on workers surveyed at baseline and endline. We estimate the following specification:

$$Y_{imct} = \beta_1 Treat_{mc} \times Endline_t + \beta_2 Treat_{mc} + \beta_3 Endline_t + \phi_c + \epsilon_{imct} \tag{4}$$

where everything is the same as Equation 3 except we introduce time, t into the model. The coefficient of interest is β_1, which is the DD estimator of the impact of working for a treated MC relative to a control MC on the change in forced labor outcomes from baseline to endline.

We additionally estimate heterogeneous treatment effects on worker outcomes by MC characteristics. We estimate the following model:

$$y_{imc} = \beta_1 Treat_m \times MCcharacteristic_m + \beta_2 Treat_m + \beta_3 MCcharacteristic_m + \phi_c + \epsilon_{imc} \quad (5)$$

where all terms are the same as before, but MC characteristic is one of the following: MC education (whether he has completed grade 10), whether he is a migrant in the city he currently works, or whether he is from the same religion, caste and home district as the worker.

4 Results

4.1 Impact of loan treatment on MC outcomes

Table 4 reports the results of the loan treatment on MC outcomes at endline from equation (1). Column 1 shows that treated MCs are 13.1 percentage points more likely than control MCs to take up the loans offered through the intervention according to administrative records, and this difference is significantly different from zero at the 1 percent level. In the MC endline survey, we also asked MCs about their loan status from a bank or formal financial institution such as our intervention loan partner in the last month. In the control group at endline, 2.6 percent of MCs have taken a loan in the past month from a bank, compared to 18.4 percent in the treatment group. This is approximately a 600 percent increase.[4]

Table 4 shows that treatment also increases formalization of MC business, particularly in terms of making more digital payments. Treated MCs are 15.5 percentage points less likely to receive payments in cash from their clients (Column 2) and more likely to receive payments through digital modes of payments, such as bank transfers, phone payments and other forms of digital wallets (not statistically significant). Treated MCs are also 18.9 percentage points more likely to pay their workers at least part of their wages using digital modes of payments compared to control MCs (Column 5). Since all MCs (treatment and control) had to have access to a bank account as a condition of the program, the increase in digital payments is not likely to be driven by an increase in the number of MCs who have access to a bank account. Instead, increasing formalization is likely to be linked to increased usage of those bank accounts because of loan take-up. The MCs who receive loans receive the payments directly into their bank accounts, and are therefore more likely to request digital payments from their clients and make digital payments to their workers.

[4]Unfortunately we did not ask current loan status from a bank at baseline.

In terms of other business outcomes, treated MCs do not appear to hire more workers (Column 6) or increase their total monthly labor bills (Column 7). They are, however, 12.7 percentage points more likely to claim that they were able to pay their workers in the past three months (Column 8), however this coefficient is not statistically significant at conventional levels. Interestingly, MC monthly business expenses (Column 9) do increase substantially by Rs 138,710 (U$1,873) per month (significant at the 5 percent level), which represents an increase of approximately 87 percent over the control group mean. These business expenses are largely comprised of expenses on materials and other construction supplies that are used in their work. Therefore, while they are not spending more on labor, they are definitely increasing expenditures on other inputs. This could reflect the fact that treated MCs are taking on more work orders or larger work orders. However, we are not able to definitively identify this in the data (as we did not ask about this). These results are robust to the addition of covariates selected using the post-double selection LASSO method (Belloni et al., 2014). These results are reported in Table A4. Table A5 reports estimates of β_1 from equation (2), and the DD results are largely consistent with the results in Table 4.

In sum, we observe evidence that the loan treatment increased loan take up and translated into increased use of digital modes of payment and a substantial deployment of loan funds into non-labor business expenses.

4.2 Impact of loan treatment on worker outcomes

We next turn to our main question of interest: how does MC access to loans impact forced labor worker outcomes? We plot estimates of β_1 from equation (3), and the control group means, in Figure 3 and show results in Table 5.[5] Panel A of Table 5 reports the impact of offering loans to MCs for the five indices described in subsection 3.3. We find that workers of treated MCs are certainly no better off on account of the loan treatment; in fact, they appear to be slightly worse off on some risk measures. The wage index that captures risks of wage withholding and delayed pay is 0.09 SDs (standard deviations) higher, the hours index is 0.11 SDs higher, and the medium risk index is 0.10 SDs higher for workers of treated MCs compared to control group MCs. While these results are statistically significant, the magnitudes are relatively small especially when compared to the results we observe for different sub-groups of MCs in the next section.

As with the MC specification, we also estimate the cross-sectional worker results with the inclusion of covariates selected using the post-double selection LASSO method. These results are reported in Table A11. The estimated coefficients for all five risk indices are positive and significantly different from zero, indicating increases of between 0.04-0.11 standard deviations in worker risk measures. When we estimate equation (4) using the DD model, the results are

[5]Table A6 through Table A10 show results for each individual indicator that make up the indices.

substantively similar (see Table A12). The estimated treatment coefficients on all indices are positive, yet relatively small.

4.3 Heterogeneity by MC characteristics

The main results suggest that the loan treatment did not improve worker outcomes; if anything they slightly worsened them. To better understand these results, we next turn to the results from equation (5), where we estimate heterogeneous treatment effects on workers by MC characteristics. Since we did not pre-specify this heterogeneity, we investigate every MC characteristic that we collected baseline data for in our sample: education completed until grade 10, whether the MC is a migrant, years of work experience in construction, and whether the MC is from the same caste, the same religion, and/or the same district as his worker. The results of the heterogeneity analysis is presented in Figure 4 and Figure 5. We plot both β_1 and β_2 from equation (5), which are the coefficients on Treat $\times$ MC Characteristic and Treat, respectively. The results show important heterogeneity in worker outcomes by MC education status and whether the MC is a migrant (Figure 4). We do not observe significant differences by any of the other characteristics (Figure 5).

MC education. The results on heterogeneous treatment effects by MC education are presented in the top panel of Figure 4 and Panel B of Table 5. We test whether workers of more educated MCs experience different forced labor outcomes, where more educated MCs are defined as those who have completed grade 10 or more (33 percent of MCs in the sample).

We find that workers of more educated MCs experience a significant reduction in three out of the five risk indices, compared to workers of less-educated MCs. These effect sizes are large. The wage, hours, and medium risk indices all decline by 0.26 SDs for workers of MCs who have completed grade 10 or more, relative to those who have not. Given these estimates, worker outcomes for these MCs improve in absolute terms in response to treatment by 0.08-0.13 SDs.

MC migrant status. We next consider variation in worker outcomes by whether the MC is a migrant himself. Twenty-two percent of MCs are non-migrants, while 78 percent are migrants. The results are presented in the bottom left panel of Figure 4 and in Panel C of Table 5. The workers of non-migrant MCs are significantly better off on account of treatment, compared to migrant MCs. Wage, hours, and medium risk indices decline by 0.16-0.25 SDs for workers of non-migrant treated MCs relative to migrant treated MCs. These workers are better off in absolute terms by 0.05-0.11 SDs, while the workers of treated non-migrant MCs are significantly worse off in absolute terms by 0.13-0.14 standard deviations.

In sum, this suggests that MCs are not simply exploiting their workers because they can. At least some treated MCs are able to use their increased liquidity to pay their workers more regularly and to improve their working conditions. We show evidence that this is true for better educated MCs and non-migrant MCs. However, it is not true for more experienced MCs: we find no significant differences in treatment effects between MCs with at least ten years of experience and those without.[6]

MC and worker similarities. We also investigate whether MCs and workers who share the same religion, caste, and/or district of origin improves worker outcomes in Figure 5. Interestingly, these similarities in characteristics do not significantly improve worker outcomes. If anything, MCs who share the same caste and district of origin as their workers, increase the forced labor risk their workers face. Anecdotally, in some discussions with our partners, it emerged that MCs might be more likely to exploit workers with whom they have stronger social connections, since those workers are less likely to quit their employment on account of delayed or withheld payments, or other indicators of forced labor. These results might be suggestive of such a story however, we note that these differences are not significantly different from zero at conventional levels.

Another possibility is that MCs are better able to exploit workers from their own district because they exert some monopsony power over them. Migrant workers might be able to find jobs in the city mainly through an MC who is from the same home district or village, and so, they may be forced to tolerate more exploitation from them. However, we find no evidence of this when comparing measures of forced labor at baseline between workers who are employed by an MC from their same district vs. a different district.

Do business operations vary? Why do we observe some differences in worker outcomes across MC characteristics? To examine potential channels that could explain the heterogeneity results, we examine variation in MC outcomes by MC characteristics in Table A13.

Across all business outcomes, more educated MCs increase the hiring of workers due to treatment status, compared to less educated treated MCs. More educated MCs are significantly more likely to report that they are able to pay their workers in the past three months (Column 3). More educated MCs also report higher expenses on both labor expenses (Column 2) and non-labor monthly business expenses (Column 4), but the standard errors are large.

In Panel B of Table A13, we examine the same outcomes for non-migrant MCs. While the number of total workers does not increase, the coeffecent on total monthly labor bills is positive (though neither coefficient is statistically significant). Non-migrant MCs also report being more likely to be able to pay their workers on time (Column 3), but this result is not statistically significant.

[6] Although younger MCs tend to have less experience and more education, experience and education are not highly correlated within our MC sample. Among the MCs who have at least ten years of work experience, 26 percent have completed grade 10 while 74 percent have not. Among the MCs who have less than ten years of work experience, 38 percent have completed grade 10 while 62 percent have not.

The impact among non-migrant MCs are similar to those for more educated MCs, though none of these results are statistically significantly. The results for MC work experience (Panel C of Table A13) do not suggest any improvement in MC ability to pay workers which is consistent with the results in Figure 4 showing no significant differences by MC experience.[7]

MCs may vary by their ability to manage additional liquidity. We expect MCs to use their additional funds to increase the scope of their business and to increase business expenses on both labor and materials. We find that more educated and non-migrant MCs are more able to do this. The additional liquidity may come with terms of repayment that MCs might find difficult to meet, leading them to further financial stress and exploitation of workers. We examine whether outcomes of the workers of MC defaulters are driving the main results by regressing the forced labor indices on the interaction of the indicators for receiving treatment and for defaulting. The results are presented in Table A14. Though suggestive, since default is endogenous, we do not find evidence that workers of these MCs are systematically worse off than the workers of non-defaulting MCs. If anything, the workers of such MCs look better off. This suggests that MCs siphoning off working capital for personal use is likely not the reason for the deteriorating labor market outcomes of their workers.

4.4 Loan take up

As discussed earlier, loan take up by MCs was relatively low. This is despite the fact that 46 percent of MCs reported facing liquidity challenges due to delayed payments by the builders who subcontract work to them. It was also the largest challenge reported by the program MCs at baseline. In this section, we show two key reasons for low loan take up. First, MCs who wanted loans were unable to get access to them due to paperwork requirements. Second, many MCs did not apply for a loan at all because they were concerned about the high perceived risk of falling behind on loan repayments on a formal sector loan.

Table 6 presents characteristics of the loans that were approved and summarizes the reasons that 47 applicants were rejected. Fifty-one percent (92 MCs) of treatment group MCs expressed an interest in the loan (not shown) and 34 percent (61 MCs) completed the application for the loan. This percentage of applicants from the total pool of treatment MCs is almost exactly the same as the share of MCs who had expressed an interest in a low-cost working capital loan at the time of the scoping study (34 percent of 520 MCs). However, only 8 percent (14 MCs) ended up being approved for the loans, and 7 percent (13 MCs) actually took out loans. These approved MCs were given 31 loans, or drawdowns on their credit lines, in total. As long as MCs were under their credit

[7] We are unable to estimate the same caste, religion, district of origin regressions because these depend on both worker and MC characteristics. Since we only consider MC outcomes here, we exclude heterogeneity based on worker characteristics.

limit and not in default on prior loans, they could take out multiple loans either sequentially or at the same time.

Among the reasons given for rejection, the most common was a low credit score or inability to provide necessary documents, which led to the application being eliminated at the first stage (38 percent). A further 21 percent failed the verification process or were unwilling or unable to register their business with the Ministry of Micro, Small & Medium Enterprises, a pre-requisite. Thirty-two percent of the MCs dropped out voluntarily at different points in the application process, which was likely linked to the onerous nature of the loan application process. Lack of access to bank accounts is not likely to have been a reason for the inability to get a loan, since all MCs had to have access to a bank account.

There were several aspects that made it challenging to approve loan applicants. One issue was that the MCs in the construction sectors operate almost entirely on an informal basis. One key requirement for accessing working capital loans is showing documentary evidence of having work orders that justify the need for working capital. However, most MCs received only informal communication from builders, developers and contractors who subcontracted work out to them about the nature of the work that they were being assigned. Rather than clear contracts, MCs would often only have some details of work orders written out on a piece of paper, which made it hard for them to claim the need for working capital funds. Many other MCs did not have basic documentation like tax registration papers, or personal identification papers or proof of address. While Gromor's list of documentary requirements was more lenient than those required by banks, even then several MCs were unable to clear this hurdle.

In Table 7 we regress applied for a loan (column 1, 3, and 5) and took loan (column 2, 4, and 6) on MC characteristics. Few demographic characteristics predict whether an MC in the treatment group applied for a loan or got approved for a loan. Interestingly, education, migrant status, caste, religion and even self-reported liquidity constraints do not predict loan applications or loan take-up. The only variable that positively predicts loan applications and approvals is if an MC at baseline reported having access to a loan from some source if needed, including banks, moneylenders, and/or family and friends. It is possible that those who could take a loan if needed may be more creditworthy, which might translate into higher take-up rates of the loans offered in this intervention.

On the demand side, there were a couple of reasons why MCs were hesitant to take up these loans. Focus Group Discussions (FGDs) with selected MCs reveal that some MCs were concerned about being reported to the credit bureau in the event of default, which is a reporting requirement for all regulated credit providers, including Gromor. Given the considerable variability with payments from builders, MCs may have been reluctant to take a chance on a low-cost loan with a large downside risk of default, rather than take up a higher cost loan from an informal source, like a money-lender.

Another reason for the loan products being relatively unpopular despite their low interest rates is that these were not traditional personal loans, which are offered with a fixed monthly repayment instalment. The Gromor loans were designed as working capital loans, whereby every drawdown was subject to approval from Gromor based on the provision of proof of working orders received from builders and contractors higher up in the hierarchy. Accordingly, monthly repayments would also be dependent on the amount that was actually sanctioned for release to the MC, and not a fixed amount through the tenure of the loan. These types of business loans are not typically made by banks to informal firms, so it is possible that lack of familiarity with such processes made it less popular among MCs.

A final reason why loans might be unpopular is that MCs may believe that the formalization that comes with taking a loan from a non-bank financial institution is the possibility of increased surveillance by tax collection authorities. Tax evasion by small businesses has been previously linked to a low demand for formalization in developing countries (De Mel et al., 2013) and in our setting, too, the possibility of being flagged for non-payment of goods and services tax could have reduced MC interest in the loan offering.

5 Conclusion

Despite the pervasive exploitation of workers globally, especially in the informal sectors of developing countries, there is limited evidence on effective interventions to reduce forced labor risk among working adults. This paper provides causal evidence on the impact of increasing liquidity for small business owners on their employees' working conditions.

We begin by rigorously measuring the prevalence of forced labor in the construction sector across two major Indian cities. This sector is considered particularly susceptible to forced labor due to its informal and fragmented nature and its reliance on migrant labor. Our findings indicate that while delayed payments and excessive working hours are common, there is little evidence of high-risk forced labor practices such as violence or coercion.

We then present experimental evidence showing that providing low-cost loans to micro-contractors does not lead to significant improvements in forced labor indicators for workers. In fact, conditions related to wages and working hours slightly worsened. However, this average effect masks important differences among types of MCs. Educated and non-migrant MCs are able to use the loans to significantly improve their business practices, resulting in better outcomes for their workers, such as timely and full wage payments and reduced working hours. Conversely, workers employed by less-educated and migrant MCs experienced deteriorated conditions. We note these results are short-term as we are evaluating impacts 4-10 months after MCs received loans.

This study is the first to provide causal evidence on the impact of loans on forced labor and offers crucial policy insights. In a business environment fraught with uncertainty, providing liquidity can impose an additional burden of loan repayments on business owners, potentially limiting the cash flow available to workers. This is reflected in the low loan uptake among MCs, despite the loans being touted as low cost. Ultimately many MCs struggled to qualify for the loans, with nearly half of applicants rejected. Some MCs also preferred more expensive informal loans from moneylenders due to their greater flexibility and lower risk of impacting credit ratings.

In conclusion, simply offering liquidity to business owners may not be sufficient to eliminate forced labor. Sustainable improvements in worker conditions likely require enhancing business owners' ability to manage uncertain cash flows more effectively.

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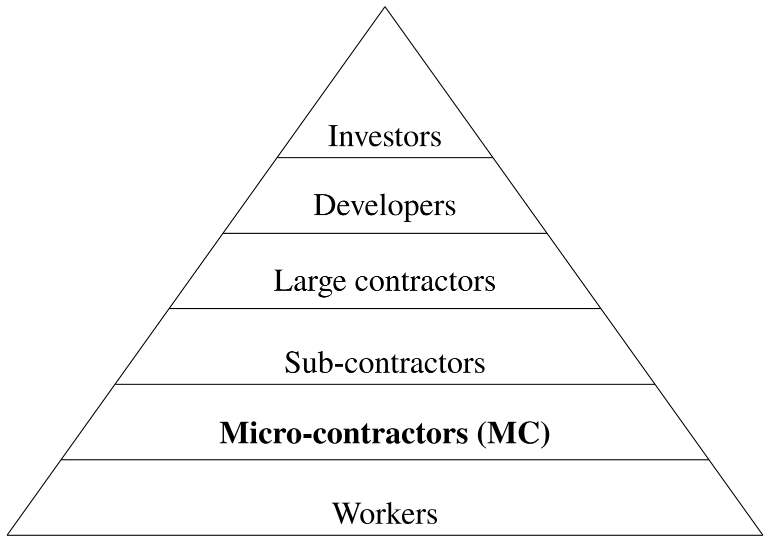
Figure 1: Structure of the Indian construction sector



Note. This figure presents the structure of the Indian construction sector. Investors fund large developers who are large, formal, corporate firms. Work is subcontracted out to large contractors who, in turn, subcontract work even further to smaller and smaller contractors. The smallest contractors in this chain we refer to as Micro-Contractors (MCs) and are responsible for conducting the work and hiring workers.
Source. Project Saksham: MEL Research Design Report. October 2021.

Figure 2: Timeline for study

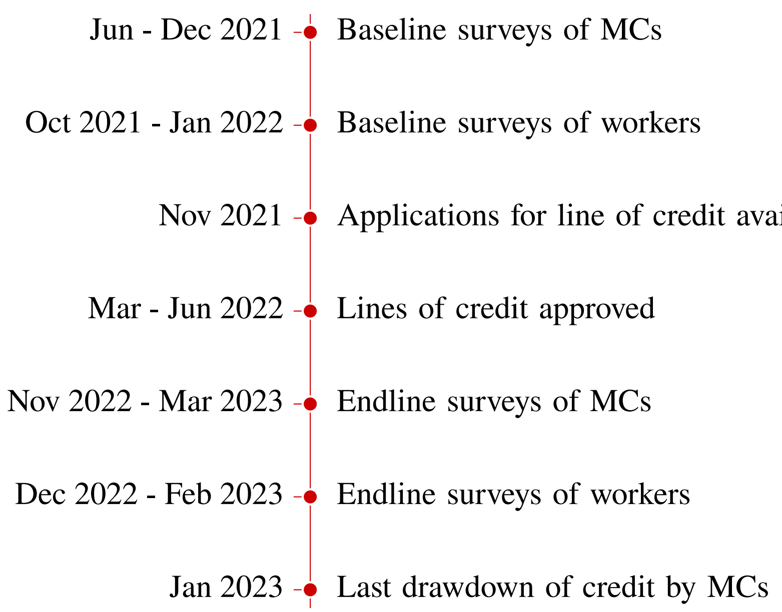
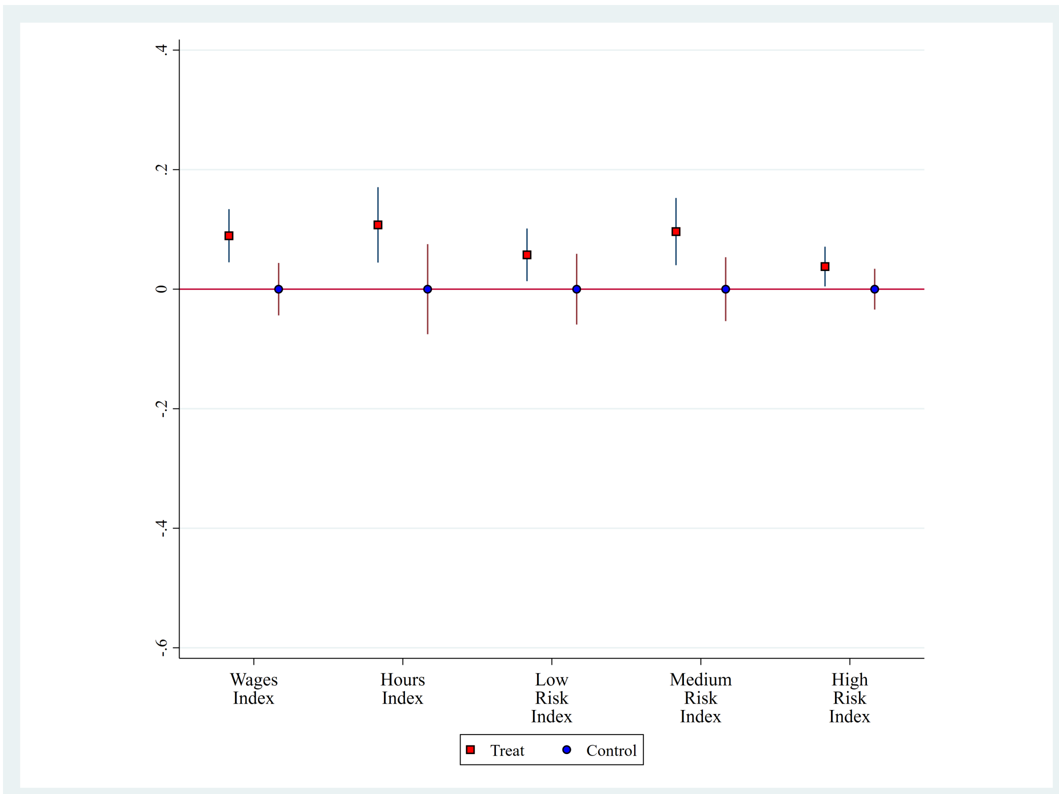
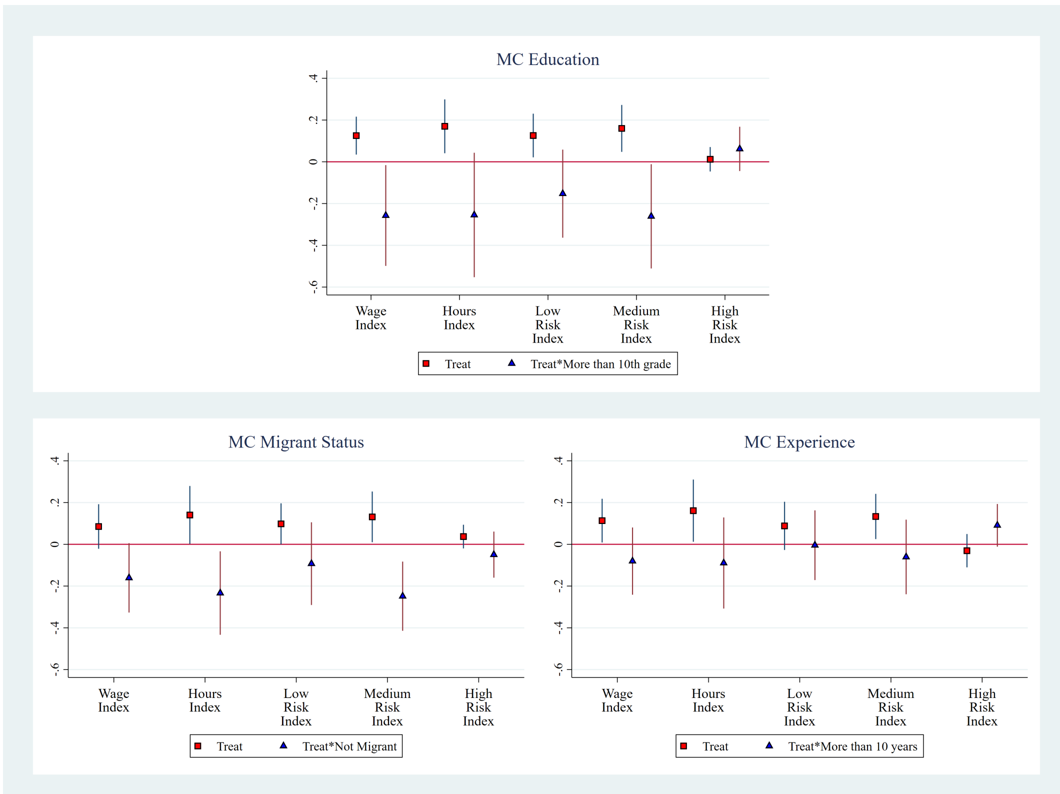


Figure 3: Impact on worker outcomes



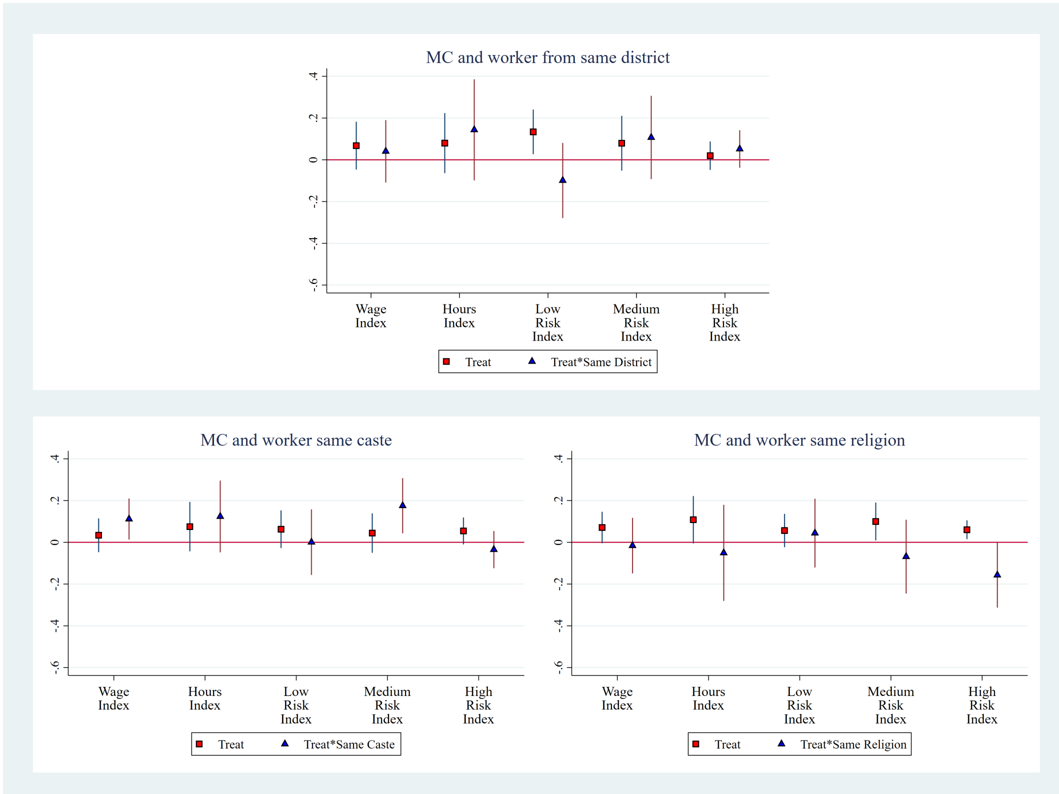
Note. This figure presents estimates of β_1 from equation (3) using endline data. Low risk is an index of 6 forced labor indicators which include irregular wage payments. Medium risk is an index of 11 forced labor indicators which include lack of rest days and working for prolonged hours. High risk is an index of 7 forced labor indicators which include threat to the worker or their family and restriction on freedom of movement. Wage is an index of 12 forced labor indicators related to the amount and frequency of wage payment received by the workers. Hours is an index of 5 forced labor indicators related to the number of hours worked and the rest days they were allowed to take. Individual indicators of forced labor in this table are defined in Table A3. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors, clustered by MC, at the 95% level are shown.
Source. Worker endline survey.

Figure 4: Impact on worker outcomes by MC heterogeneity - I



Note. This figure presents estimates of β_1 and β_2 from equation (5) using endline data, with respect to three MC characteristics: MC education (has completed at least grade 10), MC migrant status (MC is not a migrant), and MC experience (MC has worked at least 10 years). See the note in Figure 3 for a descriptions of the outcomes. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors, clustered by MC, at the 95% level are shown.
Source. Endline MC survey. Endline worker survey.

Figure 5: Impact on worker outcomes by MC heterogeneity - II



Note. This figure presents estimates of β_1 and β_2 from equation (5) using endline data, with respect to three MC characteristics: MC district (MC and worker report same home district), MC caste (MC and worker have the same caste) and MC religion (MC and worker have the same religion). MC district is taken from the MC endline because it was not asked at baseline, MC caste and religion is known from baseline. See the note in Figure 3 for a descriptions of the outcomes. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors, clustered by MC, at the 95% level are shown.
Source. Baseline and endline MC surveys. Endline worker survey.

Table 1: MC Balance Table

	Treatment	**Control**	**Difference**	**SE**
A. Baseline				
Demographics				
Delhi	0.497	0.523	-0.026	0.073
Religion				
Muslim	0.183	0.138	0.044	0.055
Hindu	0.811	0.862	-0.050	0.055
Caste				
SC/ST	0.226	0.203	0.022	0.061
OBC	0.409	0.312	0.096	0.072
General	0.354	0.469	-0.115	0.072
Outcomes				
Number of work orders	2.440	2.277	0.163	0.237
Monthly income from construction ('000)	33.000	35.769	-2.769	5.644
Total workers	43.583	36.462	7.121	6.663
Total labor bill ('000)	586.332	505.082	81.250	88.230
Mode of payment received by MCs				
Cash	0.473	0.453	0.020	0.074
Digital	0.639	0.672	-0.033	0.070
Mode of payment for workers				
Cash	0.888	0.871	0.017	0.048
Digital	0.559	0.581	-0.022	0.074
Observations	175	65		
F-test p-value	0.942			
B. Baseline values for MCs surveyed at endline				
Demographics				
Delhi	0.495	0.524	-0.029	0.092
Religion				
Muslim	0.146	0.119	0.027	0.064
Hindu	0.854	0.881	-0.027	0.064
Caste				
SC/ST	0.224	0.244	-0.019	0.079
OBC	0.398	0.293	0.105	0.090
General	0.367	0.439	-0.072	0.091
Outcomes				
Number of work orders	2.612	2.500	0.112	0.331
Monthly income from construction ('000)	36.184	41.214	-5.030	8.503
Total workers	44.058	37.476	6.582	7.674
Total labor bill ('000)	556.058	531.700	24.358	96.431
Mode of payment received by MCs				
Cash	0.471	0.415	0.056	0.093
Digital	0.637	0.707	-0.070	0.088
Mode of payment for workers				
Cash	0.861	0.825	0.036	0.067
Digital	0.554	0.675	-0.121	0.092
Observations	103	42		
F-test p-value	0.857			
C. Additional demographics for MCs collected at endline				
Age	35.644	37.333	-1.689	1.626
More than 10th grade completed	0.327	0.286	0.041	0.085
More than 10 years of experience	0.553	0.667	-0.113	0.090
Not a migrant	0.186	0.286	-0.099	0.075
Observations	104	42		
F-test p-value	0.940			

Notes. SE = standard error. MC = micro-contractor. Panel A presents baseline data on all 240 MCs that were surveyed at baseline. Panel B presents baseline data for 145 MCs that were surveyed at both baseline and endline. Panel C presents endline data on the 146 MCs from endline. The p-value in Panels A and B is from the joint F-test of all the variables in each panel, respectively. The p-value in Panel C is from the joint F-test of all the variables in both Panels B and C. *** p<0.01, ** p<0.05, * p<0.10.
Source. Baseline and endline MC surveys.

Table 2: Worker Summary Statistics

	Baseline		**Endline**	
	Treatment	**Control**	**Treatment**	**Control**
Demographics				
Male	0.86	0.85	0.94	0.94
	(0.34)	(0.36)	(0.25)	(0.24)
Age	29.84	29.74	27.67	28.89
	(9.40)	(8.94)	(8.37)	(9.20)
Married	0.67	0.65	0.57	0.58
	(0.47)	(0.48)	(0.50)	(0.49)
Time worked in construction				
Less than 3 years	0.42	0.42	0.42	0.40
	(0.49)	(0.49)	(0.49)	(0.49)
3-10 years	0.37	0.37	0.39	0.37
	(0.48)	(0.48)	(0.49)	(0.48)
More than 10 years	0.20	0.21	0.20	0.23
	(0.40)	(0.41)	(0.40)	(0.42)
Outcomes				
Monthly Income ('000)	12.47	12.36	13.07	12.84
	(5.01)	(4.67)	(22.59)	(12.07)
Hours worked per day	8.84	8.83	9.27	9.18
	(1.81)	(2.03)	(1.83)	(1.71)
Current debt with MC	0.08	0.05	0.12	0.10
	(0.27)	(0.23)	(0.32)	(0.30)
Mode of payment				
Cash	0.89	0.88	0.76	0.79
	(0.32)	(0.33)	(0.43)	(0.41)
Digital	0.16	0.15	0.26	0.23
	(0.37)	(0.36)	(0.44)	(0.42)
Observations	894	357	1136	407

Notes. MC = micro-contractor. Baseline data includes current workers of 221 program MCs, out of which 214 MCs were surveyed at baseline. Endline data includes current workers of 229 program MCs, out of which 141 MCs were surveyed at endline.
Source. Baseline and endline worker surveys.

Table 3: Prevalence of Forced Labor

	Baseline		Endline	
	Treatment	**Control**	**Treatment**	**Control**
Low risk index	.	.	0.06	-0.00
	(.)	(.)	(0.56)	(0.44)
Not paid 2x for overtime	.	.	0.52	0.49
	(.)	(.)	(0.50)	(0.50)
Not paid in full	0.00	0.01	0.04	0.03
	(0.03)	(0.09)	(0.19)	(0.16)
Not paid on time	.	.	0.12	0.07
	(.)	(.)	(0.33)	(0.26)
No extra pay or same rate for overtime	0.52	0.57	0.43	0.45
	(0.50)	(0.50)	(0.49)	(0.50)
Wage withholding	0.03	0.02	0.04	0.02
	(0.17)	(0.13)	(0.20)	(0.15)
Not paid at agreed frequency	0.02	0.02	0.07	0.09
	(0.14)	(0.15)	(0.26)	(0.28)
Any low risk indicator	0.53	0.57	0.83	0.80
	(0.50)	(0.50)	(0.37)	(0.40)
Medium risk index	-0.02	0.00	0.10	-0.00
	(0.32)	(0.43)	(0.71)	(0.41)
Not paid agreed wage	.	.	0.04	0.04
	(.)	(.)	(0.20)	(0.19)
Less pay than agreed	0.00	0.00	0.07	0.07
	(0.00)	(0.00)	(0.26)	(0.25)
Manipulation of debt	0.00	0.01	0.01	0.01
	(0.00)	(0.08)	(0.12)	(0.09)
More hours than agreed	0.00	0.01	0.07	0.06
	(0.03)	(0.08)	(0.26)	(0.24)
Work on rest day for fear	.	.	0.07	0.03
	(.)	(.)	(0.26)	(0.17)
Inability to quit	.	.	0.04	0.03
	(.)	(.)	(0.19)	(0.16)
Wage cut	0.01	0.01	0.02	0.01
	(0.11)	(0.09)	(0.14)	(0.07)
Unexplained deductions	0.01	0.01	0.04	0.02
	(0.08)	(0.11)	(0.20)	(0.15)
Could not take leave as agreed	0.03	0.03	0.15	0.20
	(0.18)	(0.18)	(0.35)	(0.40)
Work more hours than agreed	0.06	0.07	0.13	0.10
	(0.23)	(0.26)	(0.33)	(0.30)
Work on scheduled day off for fear	.	.	0.03	0.01
	(.)	(.)	(0.17)	(0.09)
Any medium risk indicator	0.10	0.10	0.35	0.38
	(0.30)	(0.30)	(0.48)	(0.49)
High risk index	0.00	0.00	0.04	0.00
	(0.00)	(0.00)	(0.52)	(0.32)
Physical violence	0.00	0.00	0.01	0.00
	(0.00)	(0.00)	(0.07)	(0.05)
Threat to self	0.00	0.00	0.01	0.00
	(0.00)	(0.00)	(0.08)	(0.00)
Threat to family	0.00	0.00	0.01	0.01
	(0.00)	(0.00)	(0.07)	(0.07)
Threat of police	0.00	0.00	0.01	0.01
	(0.00)	(0.00)	(0.09)	(0.09)

(continued)

Table 3: Prevalence of Forced Labor (continued)

	Baseline		Endline	
	Treatment	**Control**	**Treatment**	**Control**
Confinement	0.00	0.00	0.01	0.01
	(0.00)	(0.00)	(0.08)	(0.09)
No freedom of movement	.	.	0.03	0.01
	(.)	(.)	(0.17)	(0.10)
Confiscation of documents	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.05)	(0.00)
Any high risk indicator	0.00	0.00	0.05	0.03
	(0.00)	(0.00)	(0.21)	(0.18)
Wage index	-0.01	0.00	0.09	0.00
	(0.40)	(0.40)	(0.57)	(0.35)
Not paid on time	.	.	0.12	0.07
	(.)	(.)	(0.33)	(0.26)
Not paid in full	0.00	0.01	0.04	0.03
	(0.03)	(0.09)	(0.19)	(0.16)
Not paid agreed wage	.	.	0.04	0.04
	(.)	(.)	(0.20)	(0.19)
Less pay than agreed	0.00	0.00	0.07	0.07
	(0.00)	(0.00)	(0.26)	(0.25)
Not paid 2x for overtime	.	.	0.52	0.49
	(.)	(.)	(0.50)	(0.50)
Fines imposed	0.00	0.00	0.00	0.01
	(0.00)	(0.00)	(0.03)	(0.07)
Not paid at agreed frequency	0.02	0.02	0.07	0.09
	(0.14)	(0.15)	(0.26)	(0.28)
Wage withholding	0.03	0.02	0.04	0.02
	(0.17)	(0.13)	(0.20)	(0.15)
Wage cut	0.01	0.01	0.02	0.01
	(0.11)	(0.09)	(0.14)	(0.07)
No pay for overtime	0.06	0.07	0.04	0.02
	(0.23)	(0.26)	(0.19)	(0.13)
Financial penalties	.	.	0.00	0.00
	(.)	(.)	(0.04)	(0.00)
Unexplained deductions	0.01	0.01	0.04	0.02
	(0.08)	(0.11)	(0.20)	(0.15)
Any wage indicator	0.09	0.10	0.66	0.65
	(0.29)	(0.30)	(0.47)	(0.48)
Hours index	-0.04	0.00	0.11	-0.00
	(0.52)	(0.66)	(0.83)	(0.54)
More hours than agreed	0.00	0.01	0.07	0.06
	(0.03)	(0.08)	(0.26)	(0.24)
Work on rest day for fear	.	.	0.07	0.03
	(.)	(.)	(0.26)	(0.17)
Work more hours than agreed	0.06	0.07	0.13	0.10
	(0.23)	(0.26)	(0.33)	(0.30)
Work on scheduled day off for fear	.	.	0.03	0.01
	(.)	(.)	(0.17)	(0.09)
Could not take leave as agreed	0.03	0.03	0.15	0.20
	(0.18)	(0.18)	(0.35)	(0.40)
Any hours indicator	0.08	0.09	0.30	0.33
	(0.28)	(0.29)	(0.46)	(0.47)
Observations	888	352	1099	394

Notes. Baseline data includes current workers of 221 program micro-contractors (MCs), out of which 214 MCs were surveyed at baseline. Endline data includes current workers of 229 program MCs, out of which 141 MCs were surveyed at endline. At baseline, 894 workers from the treatment group and 357 workers from the control group were surveyed. In the endline, 1136 workers are in the treatment group and 407 workers are in the control group. Sample size varies due to item non-response. . indicates that the question was not asked at baseline.
Source. Baseline and endline worker surveys.

Table 4: Impact of treatment on MC outcomes at endline

	(1)	(2)	(3)	(4)	(5)
	Took loan	**Mode of payment for MCs: Cash**	**Mode of payment for MCs: Digital**	**Mode of payment for workers: Cash**	**Mode of payment for workers: Digital**
Treat	0.131***	-0.155*	0.057	-0.030	0.189**
	(0.033)	(0.089)	(0.092)	(0.070)	(0.084)
Observations	146	130	130	130	130
Control Mean	0.000	0.568	0.486	0.861	0.250
	(6)	(7)	(8)	(9)	
	Total workers	**Total monthly labor bills**	**Able to pay workers**	**Monthly business expenses**	
Treat	-1.505	-70.114	0.127	138.710**	
	(3.864)	(77.225)	(0.084)	(64.712)	
Observations	138	107	137	129	
Control Mean	24.132	400.762	0.684	157.694	

Notes. MC = micro-contractor. This table presents estimates of β_1 from Equation (Equation 1). Took loan comes from administrative Gromor data and takes the value 1 if the MC took a loan from Gromor. The remaining outcomes are self-reported from the MC endline survey. Mode of payment for MCs: Cash takes the value 1 if the MC receives some payment from clients in cash. Mode of payment for MCs: Digital takes the value 1 if the MC receives some payment from the clients through bank transfers or digital modes of payment. Mode of payment for workers: Cash takes the value 1 if the MC pays some part of their compensation in cash. Mode of payment for workers: Digital takes the value 1 if the MC pays workers some part of their compensation through bank transfers or digital modes. Total workers is the total number of workers employed by the MC in the past month. Total monthly labor bills are total expenses on labor in the past month in 1000s of Rupees. Able to pay workers takes the value 1 if the MC reported being able to pay workers in the past three months. Monthly business expense is total non-labor expenses incurred in the past month in 1000s of Rupees. Sample size varies due to item non-response. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Source. Endline MC survey. Gromor administrative loan records.

Table 5: Impact of treatment on worker outcomes at endline, by education and migrant status of MC

	(1)	(2)	(3)	(4)	(5)
	Low Risk Index	**Medium Risk Index**	**High Risk Index**	**Wage Index**	**Hours Index**
A. ITT					
Treat	0.054	0.097**	0.037	0.088***	0.109**
	(0.038)	(0.039)	(0.023)	(0.032)	(0.049)
Observations	1,450	1,401	1,470	1,428	1,426
Control Mean	-0.000	-0.000	0.000	0.000	-0.000
B. MC education					
Treat x MC More than 10th Grade	-0.153	-0.261**	0.062	-0.257**	-0.255*
	(0.107)	(0.126)	(0.054)	(0.122)	(0.151)
Treat	0.126**	0.160***	0.012	0.125***	0.170**
	(0.053)	(0.057)	(0.030)	(0.046)	(0.065)
MC More than 10th Grade	0.073	0.206*	-0.031	0.202*	0.186
	(0.094)	(0.109)	(0.034)	(0.114)	(0.134)
Observations	1,008	1,012	1,005	1,012	1,010
Control Mean	-0.017	0.011	-0.011	0.017	-0.003
C. MC migrant status					
Treat x MC Not migrant	-0.093	-0.248***	-0.049	-0.161*	-0.233**
	(0.100)	(0.084)	(0.056)	(0.084)	(0.101)
Treat	0.098*	0.131**	0.037	0.085	0.141**
	(0.050)	(0.061)	(0.029)	(0.054)	(0.070)
MC Not migrant	0.064	0.081	-0.008	0.066	0.115
	(0.080)	(0.069)	(0.049)	(0.078)	(0.072)
Observations	999	1,003	996	1,003	1,001
Control Mean	-0.017	0.011	-0.011	0.017	-0.003

Notes. MC = micro-contractor. The top panel presents estimates of β_1 from equation (Equation 3) using endline data. The middle and bottom panel presents estimates of β_1 from equation (Equation 5) using endline data. "MC more than 10th Grade" takes a value of 1 for the worker if the MC they work for has completed Grade 10 of high school, and 0 otherwise. "MC Not Migrant" takes the value of 1 for the worker if the MC they work for is not a migrant, and 0 otherwise. Sample size varies due to item non-response. The control mean is not zero in panels B and C because some workers did not have a corresponding MC who responded to the survey. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Endline MC survey. Endline worker survey.

Table 6: Loan characteristics

	Mean
Applied	0.339
Approved	0.078
Received	0.072
Among those who took out loans (N=13)	
Credit line increased	0.154
Initial credit limit ('000s)	105.000
Number of loans	2.385
At least one loan now closed with history of default	0.462
At least one loan currently in default	0.615
Among those currently in default (N=8), days since loan due	
Less than 90 days	0.000
90-180 days	0.125
More than 180 days	0.875
Among those who applied and were rejected for loan (N=47), reasons for rejection	
Does not meet criteria	0.383
MC not interested	0.319
Verification failure	0.213
Others (MC not reachable)	0.085
Observations	180

Notes. MC = micro-contactor. This table presents summary statistics on the loans offered by Gromor to the MCs. Among reasons for rejection of loan applications, does not meet criteria includes having a low credit rating score or not having necessary documents. MC not interested includes MCs who initially expressed interest in a loan but did not complete the application process. Verification failure includes MCs whose application was initially cleared subject to a due diligence process. However, the claims in their application could not be independently identified by Gromor. Other reasons include the MC moving away or not being reachable during the verification stage.
Source. Gromor administrative loan records.

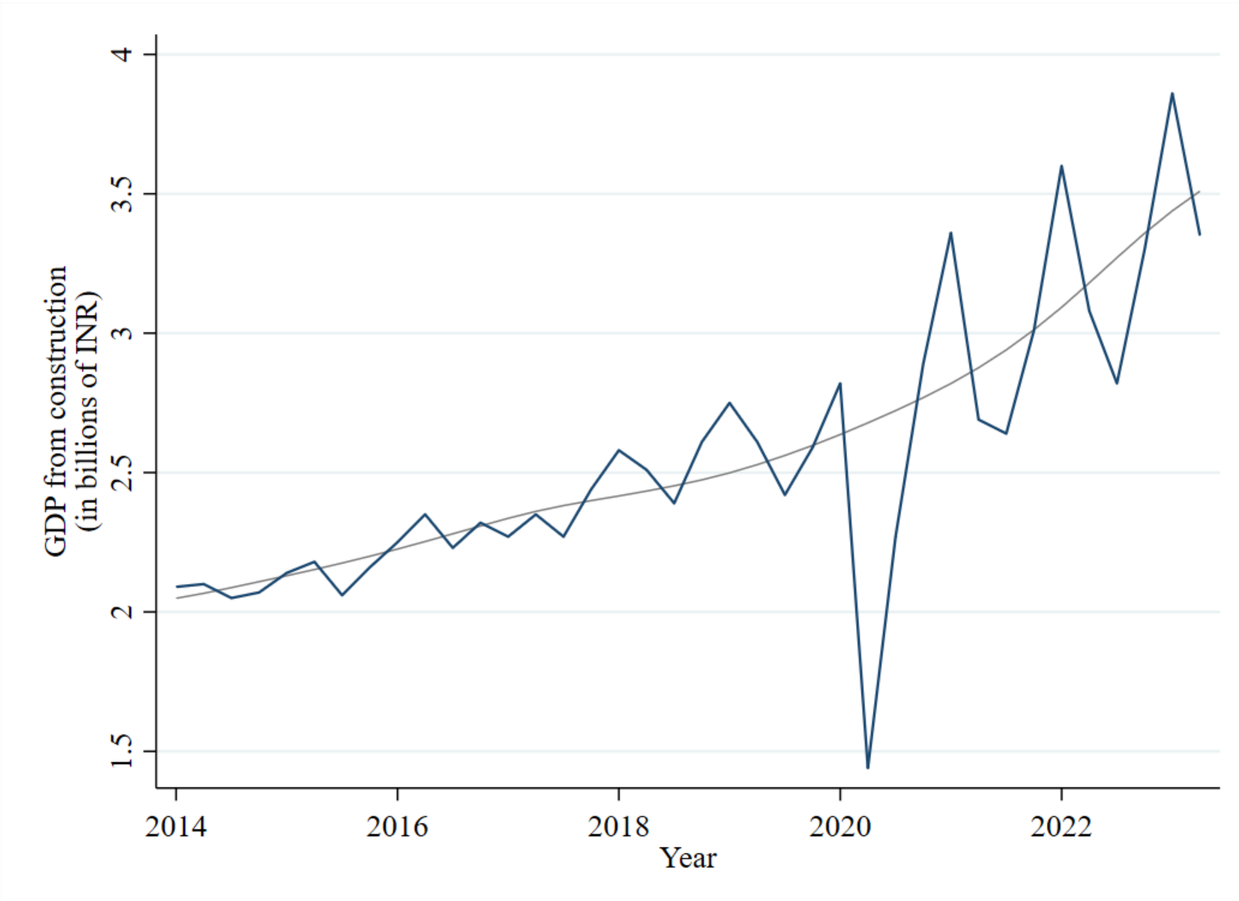
Table 7: MC characteristics that predict loan take-up

	(1)	(2)	(3)	(4)	(5)	(6)
	Applied	**Took Loan**	**Applied**	**Took Loan**	**Applied**	**Took Loan**
More than 10th grade	0.067	-0.042	0.069	-0.042	0.065	-0.045
	(0.101)	(0.056)	(0.102)	(0.056)	(0.101)	(0.055)
More than 10 years	0.134	0.012	0.134	0.012	0.145	0.022
	(0.096)	(0.053)	(0.096)	(0.053)	(0.096)	(0.053)
Not a Migrant	-0.203	-0.052	-0.198	-0.051	-0.204	-0.057
	(0.125)	(0.069)	(0.126)	(0.070)	(0.126)	(0.069)
Muslim	-0.071	-0.038	-0.072	-0.038	-0.059	-0.027
	(0.101)	(0.056)	(0.102)	(0.056)	(0.102)	(0.056)
Upper Caste	0.078	0.043	0.080	0.043	0.076	0.039
	(0.080)	(0.044)	(0.081)	(0.045)	(0.081)	(0.044)
Lack of Working Capital			0.023	0.002	0.012	-0.007
			(0.074)	(0.040)	(0.074)	(0.040)
Has Access to Loan if Needed					0.123	0.103**
					(0.085)	(0.046)
Delhi	-0.093	-0.094**	-0.094	-0.094**	-0.092	-0.092**
	(0.081)	(0.045)	(0.081)	(0.045)	(0.081)	(0.044)
Constant	0.322***	0.130**	0.310***	0.129**	0.215*	0.050
	(0.101)	(0.056)	(0.109)	(0.060)	(0.127)	(0.069)
Observations	175	175	175	175	175	175

Notes. This table presents estimates from the regression of whether an MC applied for a loan and whether the MC took a loan, as reported in administrative data, on MC characteristics. Applied takes the value 1 if the MC applied for a loan. Took loan takes the value 1 if the MC took a loan from Gromor. Education, experience, and migrant status were not asked at baseline, so they are assigned the values reported at endline, or imputed for baseline respondents who did not respond to endline. All other variables were collected at baseline. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Source. Baseline and endline MC surveys. Gromor administrative loan records.

A Appendix Figures and Tables

Figure A1: Growth in the Indian construction sector



Note. GDP = Gross Domestic Product. This figure presents the GDP from the construction sector in India from Q1 2014 through Q2 2023 in blue, and a line of best fit in gray.
Source. Trading Economics via Ministry of Statistics and Programme Implementation, Government of India.

Table A1: Analysis of attrition

	(1)	(2)
	MC attrited at EL	**MC attrited at EL**
Treat	-0.0411	-0.125
	(0.144)	(0.351)
Treat x Delhi	0.0691	0.181
	(0.149)	(0.227)
Treat x Muslim	0.0286	-0.0275
	(0.226)	(0.231)
Treat x SC/ST	0.177	0.115
	(0.185)	(0.200)
Treat x OBC	0.00889	-0.0535
	(0.171)	(0.181)
Treat x No. of Workorders		-0.0164
		(0.0376)
Treat x Income from Construction		0.00175
		(0.00317)
Treat x Total Workers		-0.0155
		(0.00989)
Treat x Total Labor Expenses		0.000907
		(0.000668)
Treat x MC Mode of Payment:Cash		0.0195
		(0.247)
Treat x MC Mode of Payment:Digital		0.0725
		(0.190)
Treat x Workers Mode of Payment:Cash		-0.146
		(0.210)
Treat x Workers Mode of Payment:Digital		0.401**
		(0.188)
Control Mean	0.359	0.356
Observations	228	210
p-value from F test of joint significance of interacted variables	0.853	0.186

Notes. This table presents estimates of the regression of whether the MC attrited at endline (EL) on baseline MC characteristics and MC characteristics interacted with treatment. MC attrited in EL takes the value 1 if a program MC did not respond to the endline survey. All regressions include baseline covariates, as well as their interactions with Treat. The p-value is from the joint F-test of all the interacted covariates (Treat*covariates) in the regression.Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Source. MC baseline and endline surveys.

Table A2: Benchmarking worker data against national data

	Worker Data		**PLFS 2021-22**	
	Mean	**SD**	**Mean**	**SD**
Demographics				
Age	29.81	9.26	30.69	6.31
Male	0.86	0.35	0.94	0.24
Married	0.67	0.47	0.65	0.48
Religion				
Hindu	0.83	0.38	0.71	0.45
Muslim	0.16	0.37	0.19	0.39
Other Religion	0.01	0.11	0.10	0.30
Caste				
SC/ST	0.27	0.44	0.35	0.48
OBC	0.37	0.48	0.42	0.49
General	0.33	0.47	0.23	0.42
Other Caste	0.02	0.15		
Education				
Illiterate or No Formal School	0.16	0.37	0.17	0.38
Grade 1st to 5th	0.14	0.35	0.15	0.36
Grade 6th to 8th	0.22	0.42	0.30	0.46
Grade 8th-12th	0.40	0.49	0.25	0.44
Some College/University	0.05	0.22	0.12	0.32
Job Characteristics				
Hours worked daily	8.84	1.88	7.41	2.88
Hours Worked Daily: Bangalore	9.61	2.26	8.92	2.10
Hours Worked Daily: Delhi	8.11	0.97	9.76	1.83
Monthly Wage	12437.73	4916.41	8887.22	8576.02
Monthly Wage: Bangalore	13439.52	5726.32	12932.76	10097.65
Monthly Wage: Delhi	11495.34	3777.04	15307.69	12087.96

Notes. SD = standard deviation. This table presents summary statistics from the sample of workers in our study as well as a sample of workers surveyed in the nationally-representative Periodic labor Force Survey 2021-22. We use data on urban workers in the construction sector under the age of 40 years from the PLFS to increase comparability with our study.

Source. Periodic Labor Force Survey, India's Ministry of Statistics & Programme Implementation. Worker baseline survey.

Table A3: Survey questions measuring forced labor indicators

Forced labor indicator	Survey question
Low risk index	
	Consider the past month. Have you faced any of these situations at work due to your MC?
Not paid 2x for overtime	- Not paid twice the usual rate for overtime
Not paid in full	- Not paid wage in full
Not paid on time	- Not paid on time
No extra pay or same rate for overtime	Consider the last month. Do you receive extra compensation if you work for extra hours (more than 8 hours) in a day?
Wage withholding	In the past month, have you been paid in full as agreed up?
Not paid at agreed frequency	Consider the past month. Are you paid in the frequency as agreed upon?
Medium risk index	
	Consider the past month. Have you faced any of these situations at work due to your MC?
Not paid agreed wage	- Not paid the agreed upon wage
Less pay than agreed	- Work for less than that was agreed upon
Manipulation of debt	- Manipulation of outstanding debt to owed MC to coerce worker to stay
More hours than agreed	- Work for more hours than agreed upon
Work on rest day for fear	- Working on rest days for fear of being fired
Inability to quit	- Inability to leave job
Wage cut	Was your wage reduced to pay off a debt you owe to the current MC ?
Unexplained deductions	Consider the past month. Were any deductions made from your salary by the current MC, that you didn't agree with or didn't understand?
Could not take leave as agreed	Consider the past month. Can you take as much leave as was agreed upon?
Work more hours than agreed	Consider the past month. Have you worked more hours than agreed upon?
Work on scheduled day off out of fear	In the past month, have you ever had to work on a rest day for fear of being fired?
High risk index	
	Consider the past month. Have you faced any of these situations at work due to your MC?
Physical violence	- Physical violence
Threat to self	- Threats against you
Threat to family	- Threats against your family
Threat of police	- Threats of denunciation to the authorities
Confinement	- Isolation, confinement or surveillance
No freedom of movement	- No freedom of movement in non-work hours
Confiscation of documents	- Confiscation of identity papers or travel documents
Wage index	
	Consider the past month. Have you faced any of these situations at work due to your MC?
Not paid on time	- Not paid on time
Not paid in full	- Not paid wage in full
Not paid agreed wage	- Not paid the agreed upon wage
Less pay than agreed	- Work for less than that was agreed upon
No pay for overtime	- Not paid twice the usual rate for overtime
Fines imposed	- Fines or financial penalties
Not paid at agreed frequency	Consider the past month. Are you paid in the frequency as agreed upon?
Wage withholding	In the past month, have you been paid in full as agreed upon ?
Wage cut	Was your wage reduced to pay off a debt you owe to the current MC ?
No extra pay or same rate for overtime	Consider the last month. Do you receive extra compensation if you work for extra hours (more than 8 hours) in a day?
Financial penalties	In the past month, has the contractor imposed any fines or financial penalties on you?
Unexplained deductions	Consider the past month. Were any deductions made from your salary by the current MC, that you didn't agree with or didn't understand?
Hours index	
	Consider the past month. Have you faced any of these situations at work due to your MC?
More hours than agreed	- Work for more hours than agreed upon
Work on rest day for fear	- Working on rest days for fear of being fired
Work more hours than agreed	Consider the past month. Have you worked more hours than agreed upon?
Work on scheduled day off for fear	In the past month, have you ever had to work on a rest day for fear of being fired?
Could not take leave as agreed	Consider the past month. Can you take as much leave as was agreed upon?

Notes. This table presents the text of the questions asked in the survey for each indicator.

Source. Worker baseline and endline survey.

Table A4: Impact of treatment on MC outcomes at endline with covariates

	(1)	(2)	(3)	(4)	(5)
	Took loan	**Mode of payment for MCs: Cash**	**Mode of payment for MCs: Digital**	**Mode of payment for workers: Cash**	**Mode of payment for workers: Digital**
Treat	0.137***	-0.161*	0.047	-0.032	0.191**
	(0.035)	(0.090)	(0.090)	(0.066)	(0.086)
Observations	146	130	130	130	130
Control Mean	0.000	0.568	0.486	0.861	0.250
	(6)	(7)	(8)	(9)	
	Total workers	**Total monthly labor bills**	**Able to pay workers**	**Monthly business expense**	
Treat	-1.207	-52.285	0.116	139.046*	
	(3.813)	(77.110)	(0.082)	(70.424)	
Observations	138	107	137	129	
Control Mean	24.132	400.762	0.684	157.694	

Notes. This table presents estimates of β_1 from equation (1) using endline data with covariates additionally included. The covariates were selected through the post double-selection LASSO method. The covariates are standardized and missing values of the covariates are imputed as the mean. See the note in Table 4 for descriptions of the outcomes. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Source. MC baseline and endline surveys.

Table A5: Impact of treatment on MC outcomes using DiD model with baseline and endline data

	(1)	(2)	(3)	(4)	(5)
	Took loan	**Mode of payment for MCs: Cash**	**Mode of payment for MCs: Digital**	**Mode of payment for workers: Cash**	**Mode of payment for workers: Digital**
Treat x Endline	0.054	-0.169	0.093	-0.047	0.212**
	(0.059)	(0.105)	(0.110)	(0.084)	(0.107)
Treat	0.078**	0.027	-0.038	0.016	-0.020
	(0.037)	(0.056)	(0.062)	(0.048)	(0.068)
Endline	0.000	0.087	-0.164*	-0.018	-0.312***
	(0.050)	(0.087)	(0.094)	(0.071)	(0.088)
Delhi	-0.081***	0.523***	-0.412***	0.150***	-0.333***
	(0.026)	(0.045)	(0.046)	(0.035)	(0.049)
Observations	386	363	363	362	362
Control Mean	0.000	0.453	0.672	0.871	0.581

	(6)	(7)
	Total workers	**Total monthly labor bills**
Treat x Endline	-8.595	-154.868
	(7.139)	(108.690)
Treat	6.880	83.826
	(6.086)	(76.404)
Endline	-12.055**	-107.210
	(5.784)	(91.911)
Delhi	-9.318**	-113.626**
	(3.986)	(57.151)
Observations	378	330
Control Mean	36.462	505.082

Notes. This table presents estimates of β_1 from equation (2) using baseline and endline data. See the note in Table 4 for a descriptions of the outcomes. Regression results for outcomes "able to pay workers" and "monthly business expense" are not presented because they were not asked at baseline. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Source. MC baseline and endline survey.

Table A6: Impact of treatment on components of the low risk index at endline

	(1)	(2)	(3)	(4)	(5)	(6)
	Not paid 2x for overtime	**Not paid in full**	**Not paid on time**	**No extra pay or same rate for overtime**	**Wage withholding**	**Not paid at agreed frequency**
Treat	0.028	0.011	0.050**	-0.026	0.015	-0.012
	(0.048)	(0.010)	(0.020)	(0.047)	(0.011)	(0.028)
Observations	1,474	1,486	1,484	1,470	1,475	1,474
Control Mean	0.491	0.026	0.072	0.455	0.023	0.088

Notes. This table presents estimates of β_1 from equation (3) using endline data for each components of the low risk index. Each individual indicator of forced labor in is defined in Table A3. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Worker endline survey.

Table A7: Impact of treatment on components of the medium risk index at endline

	(1)	(2)	(3)	(4)	(5)	(6)
	Not paid agreed wage	**Less pay than agreed**	**Manipulation of debt**	**More hours than agreed**	**Work on rest day for fear**	**Inability to quit**
Treat	0.007	0.006	0.006	0.012	0.043***	0.012
	(0.013)	(0.016)	(0.005)	(0.019)	(0.013)	(0.012)
Observations	1,486	1,492	1,481	1,491	1,487	1,484
Control Mean	0.036	0.066	0.008	0.064	0.028	0.026
	(7)	(8)	(9)	(10)	(11)	
	Wage cut	**Unexplained deductions**	**Could not take leave as agreed**	**Work more hours than agreed**	**Work on scheduled day off for fear**	
Treat	0.016**	0.018*	-0.048	0.031	0.023***	
	(0.006)	(0.011)	(0.033)	(0.025)	(0.007)	
Observations	1,458	1,469	1,465	1,439	1,467	
Control Mean	0.005	0.023	0.196	0.097	0.008	

Notes. This table presents estimates of β_1 from equation (3) using endline data for components of the medium risk index. Each individual indicator of forced labor in is defined in Table A3. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Worker endline survey.

Table A8: Impact of treatment on components of the high risk index at endline

	(1)	(2)	(3)	(4)
	Physical violence	**Threat to self**	**Threat to family**	**Threat of police**
Treat	0.002	0.006***	-0.000	0.000
	(0.003)	(0.002)	(0.004)	(0.005)
Observations	1,485	1,483	1,481	1,477
Control Mean	0.003	0.000	0.005	0.008
	(5)	(6)	(7)	
	Confinement	**No freedom of movement**	**Confiscation of documents**	
Treat	-0.001	0.021***	0.003*	
	(0.005)	(0.008)	(0.002)	
Observations	1,481	1,484	1,479	
Control Mean	0.008	0.010	0.000	

Notes. This table presents estimates of β_1 from equation (3) using endline data for components of the high risk index. Each individual indicator of forced labor in is defined in Table A3. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Worker endline survey.

Table A9: Impact of treatment on components of the wage index at endline

	(1)	(2)	(3)	(4)	(5)	(6)
	Not paid on time	**Not paid in full**	**Not paid agreed wage**	**Less pay than agreed**	**Not paid 2x for overtime**	**Fines imposed**
Treat	0.050**	0.011	0.007	0.006	0.028	-0.005
	(0.020)	(0.010)	(0.013)	(0.016)	(0.048)	(0.004)
Observations	1,484	1,486	1,486	1,492	1,474	1,485
Control Mean	0.072	0.026	0.036	0.066	0.491	0.005
	(7)	(8)	(9)	(10)	(11)	(12)
	Not paid at agreed frequency	**Wage withholding**	**Wage cut**	**No pay for overtime**	**Financial penalties**	**Unexplained deductions**
Treat	-0.012	0.015	0.016**	0.021**	0.002	0.018*
	(0.028)	(0.011)	(0.006)	(0.009)	(0.002)	(0.011)
Observations	1,474	1,475	1,458	1,470	1,468	1,469
Control Mean	0.088	0.023	0.005	0.018	0.000	0.023

Notes. This table presents estimates of β_1 from equation (3) using endline data for components of the wage index. Each individual indicator of forced labor in is defined in Table A3. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Worker endline survey.

Table A10: Impact of treatment on components of hours index at endline

	(1)	(2)	(3)	(4)	(5)
	More hours than agreed	**Work on rest day for fear**	**Work more hours than agreed**	**Work on scheduled day off for fear**	**Could not take leave as agreed**
Treat	0.012	0.043***	0.031	0.023***	-0.048
	(0.019)	(0.013)	(0.025)	(0.007)	(0.033)
Observations	1,491	1,487	1,439	1,467	1,465
Control Mean	0.064	0.028	0.097	0.008	0.196

Notes. This table presents estimates of β_1 from equation (3) using endline data for components of the hours index. Each individual indicator of forced labor in is defined in Table A3. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Worker endline survey.

Table A11: Impact of treatment on worker outcomes at endline with covariates

	(1)	(2)	(3)	(4)	(5)
	Low risk index	**Medium risk index**	**High risk index**	**Wage index**	**Hours index**
Treat	0.060*	0.097**	0.037	0.092***	0.112**
	(0.035)	(0.038)	(0.023)	(0.032)	(0.047)
Observations	1,450	1,401	1,470	1,428	1,426
Control Mean	-0.000	-0.000	0.000	0.000	-0.000

Notes. This table presents estimates of β_1 from equation (3) using endline data with covariates. The covariates are selected through the post double-selection LASSO method. The covariates are standardized and missing values of the covariates are imputed as the mean. See the note in Figure 3 for descriptions of the outcomes. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Worker baseline and endline surveys.

Table A12: Impact of treatment on worker outcomes using DiD model with baseline and endline data

	(1)	(2)	(3)	(4)	(5)
	Low risk index	**Medium Risk index**	**High risk index**	**Wage index**	**Hours index**
Treat x Endline	0.079	0.111**	0.037	0.065	0.139**
	(0.064)	(0.045)	(0.024)	(0.042)	(0.064)
Treat	-0.029	-0.028	-0.000	-0.013	-0.036
	(0.051)	(0.033)	(0.001)	(0.030)	(0.046)
Endline	-0.003	0.013	-0.000	0.014	0.005
	(0.048)	(0.034)	(0.017)	(0.031)	(0.052)
Observations	2,725	2,733	2,709	2,733	2,727
Control Mean	-0.001	0.002	0.000	0.001	-0.001

Notes. This table presents estimates of β_1 from equation (4) using baseline and endline data. See the note in Figure 3 for descriptions of the outcomes. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Worker baseline and endline surveys.

Table A13: Impact of treatment on MC outcomes by MC characteristics

	(1)	(2)	(3)	(4)
	Total workers	**Total monthly labor bills**	**Able to pay workers**	**Monthly business expenses**
A. MC education				
Treat x MC More than 10th Grade	14.003*	27.341	0.402**	75.954
	(7.841)	(161.789)	(0.191)	(131.549)
Treat	-5.831	-75.580	0.009	115.852
	(4.589)	(99.709)	(0.090)	(85.314)
MC More than 10th Grade	-2.555	85.155	-0.324*	-93.352
	(5.569)	(144.277)	(0.173)	(64.100)
Observations	138	107	137	129
Control Mean	24.132	400.762	0.684	157.694
B. MC migrant status				
Treat x MC Not Migrant	-1.983	138.704	0.262	175.189
	(10.277)	(175.722)	(0.210)	(197.303)
Treat	-0.856	-94.846	0.053	109.450
	(4.062)	(95.065)	(0.089)	(75.035)
Not a migrant	4.055	-32.660	-0.360**	51.074
	(9.580)	(139.164)	(0.179)	(89.376)
Observations	138	107	137	129
Control Mean	24.132	400.762	0.684	157.694
C. MC work experience				
Treat x MC More than 10 years	3.653	251.106	-0.102	-5.243
	(8.305)	(169.098)	(0.182)	(129.303)
Treat	-4.192	-217.708	0.193	141.735
	(7.156)	(159.447)	(0.151)	(86.597)
MC More than 10 years	-6.124	-292.898*	0.095	1.817
	(6.929)	(152.883)	(0.165)	(72.972)
Observations	138	107	137	129
Control Mean	24.132	400.762	0.684	157.694

Notes. This table presents estimates of regressions of MC outcomes on MC characteristics interacted with Treatment using endline data. In the top panel, MC outcomes are regressed on the interaction of MC education (whether the MC has completed grade 10) and treatment. In the middle panel, MC outcomes are regressed on the interaction of MC migrant status (MC is not a migrant) and treatment. In the bottom panel, MC outcomes are regressed on the interaction of MC work experience (MC has worked in construction for more than 10 years) and treatment. See the note in Table 4 for descriptions of the outcomes. Sample size varies due to item non-response. All estimations include a binary indicator for whether the MC is from Delhi. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Source. Endline MC survey.

Table A14: Impact of treatment on workers of defaulter MCs

	(1)	(2)	(3)	(4)	(5)
	Low Risk Index	**Medium Risk Index**	**High Risk Index**	**Wage Index**	**Hours Index**
Treat X Defaulter	0.065	-0.134**	-0.065*	-0.042	-0.210***
	(0.047)	(0.064)	(0.039)	(0.039)	(0.062)
Treat	0.051	0.091**	0.039*	0.056	0.116**
	(0.038)	(0.042)	(0.024)	(0.036)	(0.052)
Observations	1,488	1,493	1,485	1,493	1,491
Control Mean	-0.002	0.015	-0.000	0.016	0.004

Notes. This table presents estimates of the regression of forced labor indicators on the interaction of whether the worker's MC was assigned to Treatment and whether the MC defaulted on his loan. "Defaulter" takes the value of 1 for the worker if the MC they work for defaulted on their loan, and 0 otherwise. See the note in Figure 3 for descriptions of the outcomes. Sample size varies due to item non response. All estimations include a binary indicator for whether the MC observation is from Delhi. Robust standard errors in parentheses are clustered by MC. *** p<0.01, ** p<0.05, * p<0.10.
Source. Endline worker survey and Gromor loan administration data.