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THE CRISIS AND JOB GUARANTEES IN URBAN INDIA

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Abstract

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JEL Classification: J46, J68, L52, P25

Keywords: job guarantee, India, Urban labour markets, job vignettes, COVID-19

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The Crisis and Job Guarantees in Urban India

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September 2020

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This paper uses a new field survey of low-wage areas of urban India to show that employment and earnings were decimated by the lockdown resulting from the Covid-19 crisis. It examines workers' desire for a job guarantee in this setting. Workers who had a job guarantee before the crisis were relatively shielded by not being hit quite so hard in terms of the increased incidence of job loss or working zero hours and earnings losses. A stated choice experiment contained in the survey reveals evidence that low-wage workers are willing to give up around a quarter of their daily wage for a job guarantee. And direct survey questions corroborate this, with informal, young and female workers being most likely to want a job guarantee, and to want it even more due to the current crisis.

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1. Introduction

Job guarantee schemes have had a long history in public debate and have recently been proposed and introduced in various contexts, including in the United States by high-profile politicians Bernie Sanders and Alexandria Ocasio-Cortez, in the United Kingdom by former Prime Minister Gordon Brown and advocated by economists in public policy debates.[1] The world's largest job guarantee programme is in India. The Covid-19 pandemic has put it at the centre of growing discussion over policies to recover from the ravages of the crisis, particularly in urban areas at the "frontlines of the pandemic". The ILO has pointed to the risks faced by informal workers in developing economies, many of who have been directly affected and others whose jobs are at greater risk due to the lockdown (ILO, 2020).[2]

Informal work, including causal, temporary and subcontracted work, is a defining feature of urban labour markets in many developing countries and more recently of the "new informality" appearing in developed countries (World Development Report, 2019; Boeri et al., 2020). While certain relief packages have been put forward under Covid-19 for informal workers, measures that are needed to prevent a permanent deterioration in work and living standards are under debate. This paper evaluates and quantifies the value of a job guarantee to workers in this setting.

India typifies concerns over urban labour markets in developing economies. Even before the pandemic, Periodic Labour Force Survey (PLFS) microdata from 2017-18 shows labour force participation rates were low (48 percent) and the workforce was largely informal. Regular wage/salaried employees make up less than half of the urban workforce (48 percent in 2017-18), and the rest do their jobs in a hinterland of casual work and outsourced contracts. Even among regular employees, only 27 percent have a written employment contract. A little over half have access to some benefits (provident funds, sick pay, and health insurance) through the government or their employer. Old and new forms of informality therefore persist, leaving many without basic social protections.

[1] See Gregg and Layard (2009) on UK's job guarantee programme, Stiglitz (2019) on India's rural job guarantee as a broader policy lever and Blanchard and Rodrik (2019) on job guarantees as a policy tool for addressing inequality.
[2] https://news.un.org/en/story/2020/04/1061322

Like many developing economies, India has a young workforce - 62 percent are under 40 and most are in informal employment. Growing urbanisation and an even faster-growing young workforce pose massive challenges in developing economies and the pandemic has only acted to intensify them. There is limited work on urban labour markets in developing economies, and even less on active labour market policies in these settings (recent examples are Alfonsi et al., 2020; Banerjee and Chiplunkar, 2018; or Menzel and Woodruff, 2020). Existing evidence nonetheless shows that labour market imperfections are widespread and precarious jobs have not proven to be a stepping stone to better employment for young workers (Abebe et al., 2018).

India had one of the strictest national lockdowns to contain the spread of Covid-19 (Hale et al., 2020). It came into effect on March 24, 2020 and lasted till at least mid-May. Millions of workers in urban centres saw their work come to an abrupt halt. Many who had migrated to these areas for work were stranded without any source of income. The estimated unemployment rate tripled during lockdown (Vyas, 2020) and GDP fell by 23.9 percent in the second quarter of 2020. These big disruptions have continued to be felt widely, and recovery policies are being debated to address the livelihood crisis. Yet there is limited understanding of the actual impacts and the recovery policies that would be most effective. Regular data collection has suffered due to the pandemic and much of the analysis till now has needed to rely on projections based on pre-Covid data (see Alon et al. 2020; Bircan et al., 2020; or Gottlieb et al. 2020). Even less well-understood are the impacts on young and informally employed individuals, especially in low-income urban areas, who are most at risk of experiencing scarring effects from long-term unemployment (Machin and Manning, 1999).

To understand labour market impacts of the pandemic, this paper presents results from a survey of a random sample of over 3,000 workers aged 18 to 40 in low-income areas of urban India. It shows that Covid-19 decimated economic livelihoods in these areas. This is in line with recent work on the labour market impacts of the pandemic in developed economies (Adams-Prassl et al., 2020; Blundell and Machin, 2020; Coibion et al., 2020) where workers were hit hard. But the scale of the hit to Indian workers is an order of magnitude greater. About a quarter of workers lost their job, just over 9 percent more were not working any hours and many more were not being paid as earnings fell by 85 percent, on average, under lockdown. This is consistent with some of the findings from other recent data collection efforts which find large earning losses in various parts of India (see, for example, Afridi et al., 2020; Barboni et al., 2020; Bhalotia et al., 2020; Kesar et al., 2020; or Lee et al., 2020) and in other developing economies for which recent data are available (see Bandiera et al., 2020, for villages and slums in Bangladesh; Jain et al., 2020, for South Africa; or Mahmud and Riley, 2020, for rural Uganda).

Having shown the scale of these employment and earning losses caused by the pandemic, the paper moves on to examine job guarantees, which are being considered as an active labour market policy that could assist economic recovery in urban places. India already runs the world's largest jobs programme under its Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), which entitles rural households to demand a 100 days of work a year from the government. A few state governments have introduced an urban equivalent of MGNREGA, though budgets are relatively small. The central government has recently announced plans for an urban job guarantee in small towns and cities to address the crisis (NDTV, 2020). Proposals to operationalise it range from wage subsidies for employers to direct employment by public institutions (Kulkarni and Ambasta, 2020; Dreze, 2020).

A large literature has examined India's existing rural employment guarantee scheme (Sukhtankar, 2017, Ravallion, 2019), but there remains a dearth of knowledge on labour market policy in urban labour markets. While agriculture and the rural job guarantee have provided some respite in villages during the crisis, low-income individuals working in urban areas have seen little assistance. An urban job guarantee has scope to help these workers recover economically from the pandemic. Its self-targeting feature can be expected to be effective in identifying individuals who are being pushed into urban poverty and who would not normally be covered under poverty alleviation programmes (see Besley and Coate, 1992). Yet little is known of the extent to which workers would value a guarantee of work.

The survey was specifically structured to examine how presence of a job guarantee affected the employment and earnings impacts of the lockdown and how much workers are willing to pay for a job guarantee at work. On the first of these, and importantly, the big labour market losses that resulted from the crisis were strongly mediated for workers who had a job guarantee before the crisis. They were relatively shielded by not being hit quite so hard in terms of the increased incidence of unemployment or working zero hours and earnings losses.

Evidence on the second question, valuing a job guarantee, comes from a discrete choice survey experiment that elicited preferences and willingness to pay for a guarantee of a hundred days of work from random variations in wages offered for jobs with and without a job guarantee. The experiment builds on prior research in labour economics, where there is a long tradition of using these kinds of survey questions to elicit worker preferences for non-pecuniary job attributes. For example, Farber (1983) draws on hypothetical employment survey questions to separately identify frustrated demand for unions from a lack of desire for a union job. A more recent, growing literature goes further to determine the valuation of non-pecuniary benefits and costs through experimental designs in surveys (for example, Datta, 2019; Eriksson and Kristensen, 2014; Mas and Pallais, 2017, 2019; and Wiswall and Zafar, 2018).

The findings from the experiment show that, despite the crisis resulting in large numbers of workers not working and many experiencing staggeringly high earnings losses, there is a sizable willingness to pay for a job guarantee among workers who did not have one before the C19 induced lockdown. Low-wage workers are willing to give up around a quarter of their daily wage for a job guarantee. And other survey questions corroborate this significant valuation, with informal, young and female workers being most likely to want a job guarantee, and to want it even more due to the current crisis.

2. Survey Design and Data Description

The survey was conducted between 14 May and 8 July 2020, with the aim of understanding the impact of Covid-19 on work in urban areas. India offers a unique setting for its large informal workforce, young population, restrictive lockdown and policy relevance for job guarantees. The survey was designed to understand the experiences of younger individuals, aged between 18 and 40, who are over-represented in informal jobs and at most risk of scarring effects from long-term unemployment that would arise under a weak recovery from the pandemic.

The survey was conducted on a random sample of over 5,500 individuals from fifty low-income urban ward clusters in each of the three states of Bihar, Jharkhand and Uttar Pradesh. These are some of the poorest states in India with many areas closer in poverty levels to those in sub-Saharan Africa

(Global Multidimensional Poverty Index Report, 2018). Lists of individuals were collected from field visits to local markets and local businesses (providing essential goods and services) during opening hours. Face-to-face interviews were not feasible due to lockdown restrictions. A random sample of 30 individuals per ward cluster were therefore interviewed by phone. The survey was primarily administered in Hindi by trained enumerators. English translations were available as needed.

The survey collected information on employment status and earnings of employed individuals, covering 3045 employees or informal individuals who were in work before lockdown. They form the relevant group for studying Covid-19 impacts and job guarantees (see Appendix Table A1 for more detail on sample selection). Just over a third were employees in private businesses, co-operative societies or trusts while the rest were informal workers, including casual workers (e.g. daily labourers), those employed by private households (e.g. cooks, cleaners) and those employed by a single private individual (e.g. personal driver).

The survey builds on and extends previous surveys on Alternative Work Arrangements in various countries including Germany, Italy, the United Kingdom and the United States (Adams-Prassl et al., 2020; Boeri et al., 2020, Datta 2019). It contains standard questions on demographics, earnings and employment and questions on alternative work arrangements and job guarantees, which are usually not covered in detail in labour force surveys or real-time data sources. The job guarantee questions are framed as a guarantee of a minimum number of days of work during the year. This is motivated by two key reasons. First, India's MGNREGA guarantees a 100 days of work to rural households seeking work from the government. Examples and proposals of an urban job guarantee also take similar forms (for example, Madhya Pradesh's experimental urban job guarantee scheme for young marginalised workers and the State of Working India (2018) proposal for a national urban employment guarantee). Second, daily wages are a standard payment form and minimum wage laws in India specify a daily wage rate.

The job guarantee part of the survey instrument includes direct survey questions on whether the individual would like a job guarantee and whether Covid-19 altered that choice. To provide a quantification of their preferences in monetary terms, it conducts a job choice randomised experiment using a vignettes research design, where workers choose between two jobs that are identical in all respects except one offers a job guarantee at a wage that is randomly reduced relative to another job which offers no guarantee. The non-experimental and experimental questions about desire for a job guarantee are:

i) *Would Like Job Guarantee* - Would you like a guarantee of at least 100 days of work in the year?

ii) *More Likely to Want Job Guarantee Due to Corona Lockdown* - Has the Corona lockdown made you more or less likely to want a job which has a work guarantee of 100 days in the year?

iii) *Choice Experiment*. Assume that for one reason or another you are looking for a new job. You soon receive two job offers and must decide which one to choose. The jobs are identical in every way except for the features which are emphasised. Which job do you prefer: A or B?

The first question on whether workers would like a job guarantee refers to workers' baseline employment. The second question refers to whether desire for a job guarantee has changed before and after lockdown, and the change nature of the question also fixes other job attributes (such as job type, work scheduling, amount of work). The choice experiment holds all job attributes constant except the wage-guarantee profile. The Usual Wage in the choice experiment is obtained from the daily wage in pre-Covid employment and the Markdown on Usual Wage is randomly assigned from a zero percent markdown up to 40 percent. (See Appendix Table A1 for details, including a visual representation of the job vignettes, as it appears on enumerators' screens).

3. Labour Market Outcomes during the Lockdown

This section begins with a description of the prevalence of job guarantees in the labour market, then moves on to study differences in employment and earnings outcomes for workers who did or did not have a job guarantee in their pre-Covid employment.

Who has a job guarantee?

Exhibit 1 presents the shares of workers that have a job guarantee in work by various demographic and job characteristics. 17.5 percent of all workers had a guarantee of a minimum number of days of work in a year. Employees were more likely to have a job guarantee (22.3 percent) than informal workers (15.9 percent). Younger and more educated workers (with educational attainment higher than 10th standard) were more likely to have a job guarantee. And female workers were more likely than male workers to have a job guarantee, if they were informally employed. The job guarantees are primarily provided by employers (24.6 percent) and job contractors or temporary agencies (36.6 percent), others a consequence of workers having a side business of their own or in their family and workers having rural domicile making them eligible for the rural job guarantee.

Exhibit 1 also shows that urban areas which continued to see a partial or complete lockdown, after the strict national lockdown ended on 3rd May, had higher shares of workers with job guarantees. This is unsurprising as larger towns and cities were more likely to remain under an extended lockdown and these areas also have more formal job opportunities. Workers, who were in jobs where a greater share of tasks could be done from home, were also more likely to have a guaranteed number of days of work. This is true for both employees and informal workers. These pre-lockdown differences raise interesting questions about how lockdown may have affected work differently for those with and without a job guarantee.

Do employment and earnings impacts of the crisis differ by whether workers have a job guarantee?

Exhibit 2 shows summary statistics to offer an initial descriptive analysis of the employment and earnings impacts. It does so by comparing before and after lockdown outcomes across all workers and between those who did and did not have a job guarantee before the pandemic. Workers were asked to report their employment status in the week before the survey. Panel A shows that almost a quarter of workers, who all had a paid job before the pandemic, lost their jobs during the lockdown. This unemployment rate however masks the true level of worklessness that arose from the pandemic. Another 9.4 percent of workers, who continued to be employed, reported working zero hours in the week before the survey. Consequently, the urban rate of not working ticked up to a huge 33 percent.

Panel B of Exhibit 2 shows staggeringly large earning losses experienced by urban workers. While many countries have put in place generous furlough provisions, India did not and so differs in that urban workers experienced a decimation of their economic livelihoods. April is the only full month of the strict national lockdown in India. Comparing average monthly earnings of workers in January-February to those in April, urban workers saw their earnings fall by an enormous 85 percent, on average. This obviously includes a sizable number of people who were not paid despite having a job. Panel C shows that those who continued to be "in work" saw a slightly smaller – 81 percent - drop in earnings on average. Those who did get paid something during the time naturally saw much smaller earnings losses; less than a quarter of their pre-Covid earnings were lost, as shown in Panel D.

The Table also makes it clear that workers who had a job guarantee in their pre-Covid employment were protected from both job and earning losses. Even though workers without a job guarantee had higher earnings before the pandemic, they were 9.5 percentage points more likely to be out of work, either through job losses (3.4 percentage points higher) or through zero hours at work (6.2 percent more likely). They suffered much greater earning losses – Rs 7,000 monthly or 87 percent of average pre-Covid earnings, compared with Rs 5,550 monthly or 75 percent of their pre-Covid earnings for workers who had a job guarantee. Being in work or getting paid did not alter this pattern of higher earning losses for workers lacking a job guarantee. Their losses if in work were 83 percent compared to 70 percent for workers who had a job guarantee and 25 percent compared to 15 percent for those who got paid.

Statistical estimates

Exhibit 3 presents a more systematic analysis of employment and earnings losses. For worker i, the change in employment and earning outcomes can be defined as $\Delta Y_{i1} = (Y_{i1} - Y_{i0})$, with Y being the relevant labour market outcomes and the 1 and 0 subscripts respectively referring to post-lockdown and pre-lockdown time periods. These can be related to whether the worker had a job guarantee (G) and other variables (described below) in the baseline through the following regression:

$$\Delta Y_{i1} = \alpha + \beta G_{i0} + \sum_{d=1}^{D} \gamma_d D_{di0} + \sum_{l=1}^{L} \gamma_l L_{li0} + \varepsilon_{i1} \qquad (1)$$

The main estimand of interest in (1), β, therefore estimates differences in post-Covid employment and earnings outcomes across workers that had a job guarantee in their pre-Covid job compared to those that did not conditional upon which demographic/job (D) and lockdown (L) independent variables are included (ε is an error term).

Demographic/job pre-crisis variables include age in years, an indicator for female workers, an indicator for education lower than 10th standard, and an indicator for informal workers. Pre-lockdown characteristics are measured as the location of the workplace and the ability to work from home in pre-Covid jobs. After the strict national lockdown ended in early May, a more targeted approach was taken so that some level of normal activity could resume. The country was divided into zones according to the number of confirmed cases to identify infection hotspots. Green zones were allowed to resume most activities that had been restricted during lockdown. Orange zones, red zones, buffer zones and containment zones were more restrictive in terms of the types of activities that were allowed to resume. To account for differences in the lockdown intensity, an indicator for whether pre-lockdown workplaces were located outside of a green zone is included. Lockdown restrictions might be less important for employment outcomes of workers who were able to do some share of their work tasks from home. Accordingly, an indicator for the worker's ability to work from home is included to account for differences in lockdown exposure (Dingel and Neiman, 2020). Further, to account for time-invariant differences across locations, state and big city fixed effects were included (Table A1 of Appendix).

Exhibit 3 shows a range of estimates of equation (1). The upper panel examines employment losses from Covid, reporting equations for job loss, zero hours and not working with demographic/job variables included (specifications (1), (3) and (5)), and then additionally including the lockdown variables (specifications (2), (4) and (6)). The lower panel reports analogous specifications for earnings losses, also including pre-lockdown earnings to control for scale effects. To assess how the large estimated job guarantee raw mean differences presented in the earlier descriptive analysis are affected by inclusion of the two sets of independent variables, the β coefficients on the job guarantee dummy variable can be directly compared to the numbers in Exhibit 2.

Those raw differences remain largely unaffected by the inclusion of demographic and lockdown characteristics and, if anything become slightly larger in magnitude (in absolute terms). Having a job guarantee before the pandemic reduced the probability of job loss by a sizable 5 percentage points. It also reduced the chances of being on zero hours by 6.6 percentage points and of not working by 11.6 percentage points. Workers without a job guarantee experienced much bigger earning losses, with the full sample losing between Rs 929 and Rs 984 (specifications (7) and (8)) on average. The earning loss protection from a job guarantee is also seen for those who continued to be in work (specifications (9) and (10)), but loses statistical significance for those who got at least some pay during the lockdown (specifications (11) and (12)).

The γ_d and γ_l coefficients are also of interest in their own right, in particular in how the lockdown variables themselves impact on employment and earnings, and how their inclusion affects the estimated coefficients on the demographics. Exhibit 3 reveals worse employment effects for younger and relatively educated workers, but no such impact on earnings losses, with the exception of the group with at least some pay. Younger workers within the latter group suffered bigger losses of earnings. There are no marked differences between men and women. Informal workers do better on employment, with far fewer working zero hours, but they take a big hit on experiencing higher earnings losses.

The lockdown variables enter the employment and earnings equations as one would expect if they act as a supply shock induced by the lockdown. People who are able to work from home are strongly insulated against employment and earnings losses and those employed in workplaces that were located in areas outside green zones suffered more in terms of work and earnings. But, as already noted, the employment and earnings protection from the job guarantee remains robust to their inclusion. Additional lockdown variables, namely industry and firm size, were also included to account for differences in lockdown restrictions across industries and labour law differences across firms (Appendix Table A2). Their inclusion does not alter any of the key results. The only difference of note arises from the coefficients on the lockdown zone losing some precision. The job guarantee results remain intact and, if anything, are a little stronger.[3]

4. The Value of a Job Guarantee in the Crisis

The previous section presented strong and robust evidence that workers who lacked a job guarantee before the C19 pandemic hit, experienced larger employment and earning losses on lockdown. The pandemic has spread further in India and the economy is taking time to recover. There are concerns that many workers will continue to face economic hardship, especially in sectors that remain more shut down, and that in the absence of a policy response will be placed on a trajectory heading towards long term worklessness.[4] New policies, primarily an urban job guarantee, are therefore

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[3] For example, in specifications (11) and (12), the magnitude (in absolute terms) of the earnings loss reduction from having a job guarantee rises and the coefficient regains statistical significance (at the 5 percent level).

[4] The survey also asked about expectations in the next three months. Respondents showed a large degree of pessimism overall, as 80 percent of workers expected to lose their current job, be working for fewer hours or

being considered at local, state and central levels to prevent a new set of previously employed workers from being pushed into urban poverty. As these debates progress, better understanding is needed of the value, if any, that workers place on having a job guarantee.

Do workers value a job guarantee?

The survey design enables several pieces of evidence to be harnessed on the extent to which workers value a job guarantee. The first comes from a job guarantee discrete choice experiment implemented in the primary survey of workers. The vignettes approach it adopts has been widely used in studies of compensating differentials and provides a benchmark for evaluating the value of non-pecuniary job attributes (see, for example, Viscusi and Aldy, 2003; or Mas and Pallais, 2017, 2019). It is particularly suited to valuation of a job guarantee, which is a well-defined job attribute that people understand.

In the stated preference experiment, workers were offered a choice between two jobs, one at their usual wage rate without any number of guaranteed days of work per year and the same job at a lower wage rate but with a guarantee of a minimum hundred days of work per year. The jobs are otherwise identical, and they differ only in these wage-guarantee dimensions. The wage offered under the job guarantee equals (1- Markdown/100) × Usual Wage, where the Markdown on wages is randomly generated from integer values [0, 40]. To fix ideas through an example, an individual who has a usual wage of Rs 300 a day and who gets a random draw of 20 for the markdown would be offered a wage of Rs 240 a day under the job guarantee.

There are at least two key advantages of using this kind of experiment to quantify the value of a job guarantee. A first advantage is that it provides a monetary value that goes beyond qualitative measures, and does so by posing a counterfactual scenario with which to compare the job guarantee. A second advantage is that alternative ways of quantifying could be biased and hypothetical data can address some of those concerns. Typically, Willingness To Pay (WTP) parameters can be estimated with observational job choice data. These could be biased if omitted non-pecuniary benefits and costs

continue to be unemployed, whilst the other 20 percent either said their job would be unaffected or prospects will improve. There was less pessimism for those with a job guarantee at 68 percent on things worsening as compared to 82 percent amongst those without a job guarantee.

associated with a job are related to the observed job attributes, for example, to earnings through compensating differentials. Another source of bias would be if employers choose the set of jobs available to workers, which seems to be an important feature in studies of the gig economy, and in which case the estimated parameters reflect employer requirements or discretion rather than job preferences of workers. Hypothetical experiments avoid some of these issues - the trade-off between non-pecuniary and pecuniary attributes is explicitly made and the job choice set is given randomly by the experiment for the attribute under consideration. This minimizes concerns regarding correlation of job characteristics with unobserved tastes (see Wiswall and Zafar, 2018, and Appendix).

Exhibit 4 presents a graphical exposition by plotting the proportion choosing the job guarantee option against the randomly allocated wage markdown offered to survey respondents in the choice experiment. The Figure is drawn for the set of workers who do not have a job guarantee at work (2,512 of them), as this is the key group of policy interest. The x-axis is the negative Markdown/100 that is randomly assigned to individuals and ranges at 0.01 intervals between -0.4 to 0. (Appendix Table A3 contains randomisation tests by key demographic characteristics). The y-axis is the proportion of workers who chose the job guarantee offer over the job with a higher wage and no guaranteed days of work, holding all other job attributes fixed. The scatter plot and the fitted line reveal a downward slope that shows Indian urban workers are willing to take a wage cut to obtain employment with a job guarantee.

Workers' marginal WTP for a guarantee can be calculated from the logit estimates that underpin the line shown in the Figure. The WTP measure is derived from the estimated coefficients of this logit regression of whether an individual chooses the job guarantee offer on the randomly assigned wage markdown. The median (and mean for the case of a logit) WTP percentage is the ratio of the estimated constant coefficient to the coefficient on the wage markdown ($[(\beta_G/\beta_W) \times 100]$ in the notation of the the Appendix exposition). For all workers without a job guarantee, the median willingness to pay is estimated to be 25.5 percent, showing that workers are willing to take a fairly sizable wage cut for a guarantee of 100 days of work.

Exhibit 4 also reveals that, whilst a sizable majority near 70 percent do, not all workers offered a job guarantee even at a zero wage reduction choose the position with a job guarantee. There are various reasons why this might be, like stigma being associated with guarantees or inability to work in the types of jobs that have one. This was explored in the survey by asking people who said they would not like a job guarantee why that was their response. They either said they do not need it (56.4 percent), have domestic commitments that prevent them from taking one (24.1 percent and mostly dominated by female workers), would want to do other types of work (16.4 percent), are a student (4.6 percent) or are ill or disabled and unable to take one (1.7 percent). Informal workers, who do not want a job guarantee, are more likely to not need one (60.7 percent v 56.4 percent for employees) and less likely to be students (2.2 percent v 10.1 percent for employees).[5]

Demand for a job guarantee from experimental and non-experimental evidence

Exhibit 5 systematises the WTP analysis in more detail, together with other estimates of desire for a job guarantee from different (non-experimental) questions asked in the survey. Columns (1) and (2) show the estimated willingness to pay for a job guarantee as a percentage and in Rupees at the usual median daily wage for different groups of workers. As already noted in the discussion of the Figure in Exhibit 4, the median willingness to pay for a job guarantee is 25.5 percent of usual wages across all workers. This corresponds to Rs 81 daily.

The survey design also elicited direct responses to questions about whether workers who did not have a job guarantee would like one, and whether their experiences under lockdown changed whether or not they would like a job guarantee. Responses to the direct survey questions on wanting a job guarantee, shown in columns (3) and (4), align well with the experiment - 76.8 percent of workers without a job guarantee say they would like a guarantee of at least 100 days of work in the year.[6] As depicted in columns (5) and (6) the pandemic has made over a third of workers more likely to want a job which has a guarantee of a hundred days of work in the year.

Preferences for a job guarantee are likely to vary across demographic groups. As the markdown is randomised, inclusion of demographic variables into a job choice regression does not alter the slope of the willingness to pay with respect to the wage markdown in Exhibit 4 (see column (1) of Appendix

[5] See Table A4 of the Appendix.
[6] The reasons these workers would like a job guarantee were: due to the pandemic and lockdown (69.7 percent); there not being enough work available (34.9 percent); and/or there not being enough job security otherwise (46.7 percent). (Multiple answers were permitted).

Table A5). The take-up rate however can vary across demographic groups, which result in differences in valuations. Exhibit 5 therefore examines these variations in the WTP for a job guarantee. It shows younger workers and female workers have a higher willingness to pay for a job guarantee. Their responses to the non-experimental survey questions corroborate this and also show them to be: i) much more likely to want a job guarantee; and ii) to want it even more since the pandemic.

Low and high education workers have similar WTP, but low education workers are more likely to want a job guarantee. Similarly, employees and informal workers have similar WTP, but the amount that employees are willing to pay is much higher because their median wages are also higher. Informal workers however are much more likely to say they would like a job guarantee (78.8 percent relative to 70.4 percent). Importantly, informal and low-education workers have become much more likely to want a job guarantee due to the pandemic. Informal workers are 15.2 percentage points more likely than employees and low education workers are 8.9 percentage points more likely than higher education workers to want a job guarantee due to the pandemic.[7]

5. Conclusion

This paper examines job guarantees and the low wage labour market in urban India during the Covid-19 crisis. It uses newly collected field data to undertake a before/after lockdown analysis of labour market outcomes. This shows big employment and earnings losses occurred for workers due to the crisis. The analysis also reveals that workers who had a job guarantee before the crisis were relatively shielded by not being hit quite so hard in terms of the increased incidence of unemployment or working zero hours and earnings losses.

The protective nature of a job guarantee is further analysed through survey questions and a randomised experiment using a vignettes research design, where workers were able to pick between otherwise identical jobs that did and did not offer an employment guarantee. In both, workers are shown to significantly value a job guarantee. From the experiment, they would be willing to pay on average

[7] Regressions that enter all the individual characteristics as independent variables are reported for the job guarantee choice experiment, and the two survey questions on whether individuals would like a job guarantee or whether they have become more likely to want one under the pandemic in Appendix Table A5.

just over a quarter of their daily wage to be able to get a guarantee of a minimum days of work. Young workers and female workers have higher willingness to pay for a job guarantee. The non-experimental survey evidence strongly corroborates that Indian low-wage workers have a desire for guaranteed work. Informal workers and female workers are more likely to want a job guarantee, and to want it even more due to the current crisis.

Overall, the crisis has raised the demand for a job guarantee for those who did not have one before lockdown. The fifth of workers with a job guarantee were protected from the worst crisis in their working lives by their job guarantee. This has clear ramifications for labour market policies in the Indian context, but also more widely in other countries where labour market outcomes have been hit very hard by the pandemic. Informal workers across the developing world have seen their economic livelihoods plummet due to the pandemic. While transfers have provided some relief, the challenge of providing decent work to prevent displacement and longer-term unemployment remain high on the agenda. Job guarantees are a potentially important policy lever, not least because workers significantly value them for the work, income and security that they provide.

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Exhibit 1: Job Guarantee, Pre-Lockdown

	All	Informal	Employee
All	0.175	0.159	0.223
Aged≤25	0.191	0.180	0.216
Aged>25	0.165	0.148	0.228
Female	0.195	0.191	0.201
Male	0.168	0.147	0.235
Education≤10th standard	0.162	0.151	0.226
Education>10th standard	0.208	0.195	0.221
Lockdown zone	0.195	0.171	0.262
No lockdown zone	0.132	0.133	0.129
Able to work at home	0.273	0.273	0.274
Unable to work at home	0.167	0.151	0.216
Sample size	3045	2268	777

Exhibit 2: Employment and Earnings, Pre-Lockdown and Lockdown

	All	Job Guarantee	No Job Guarantee	Gap (Standard Error)
	(1)	(2)	(3)	(4) = (3)-(2)
A. Employment				
Job loss	0.236	0.208	0.242	-0.034 (0.019)
Zero hours	0.094	0.043	0.105	-0.062 (0.011)
Not working	0.330	0.251	0.347	-0.095 (0.021)
Sample Size	3045	533	2512	3045
B. Earnings, All				
Monthly earnings, pre-lockdown	7954	7392	8074	-682 (247)
Monthly earnings, lockdown	1206	1844	1070	774 (182)
Percent earnings loss	85	75	87	
Sample size	3045	533	2512	3045
C. Earnings, Working				
Monthly earnings, pre-lockdown	8081	7380	8251	-872 (286)
Monthly earnings, lockdown	1551	2236	1385	851 (245)
Percent earnings loss	81	70	83	
Sample size	2040	399	1641	2040
D. Earnings, Paid				
Monthly earnings, pre-lockdown	8384	9090	8165	925 (706)
Monthly earnings, lockdown	6472	7690	6094	1597 (741)
Percent earnings loss	23	15	25	
Sample size	489	116	373	489

Notes: Standard errors in parentheses.

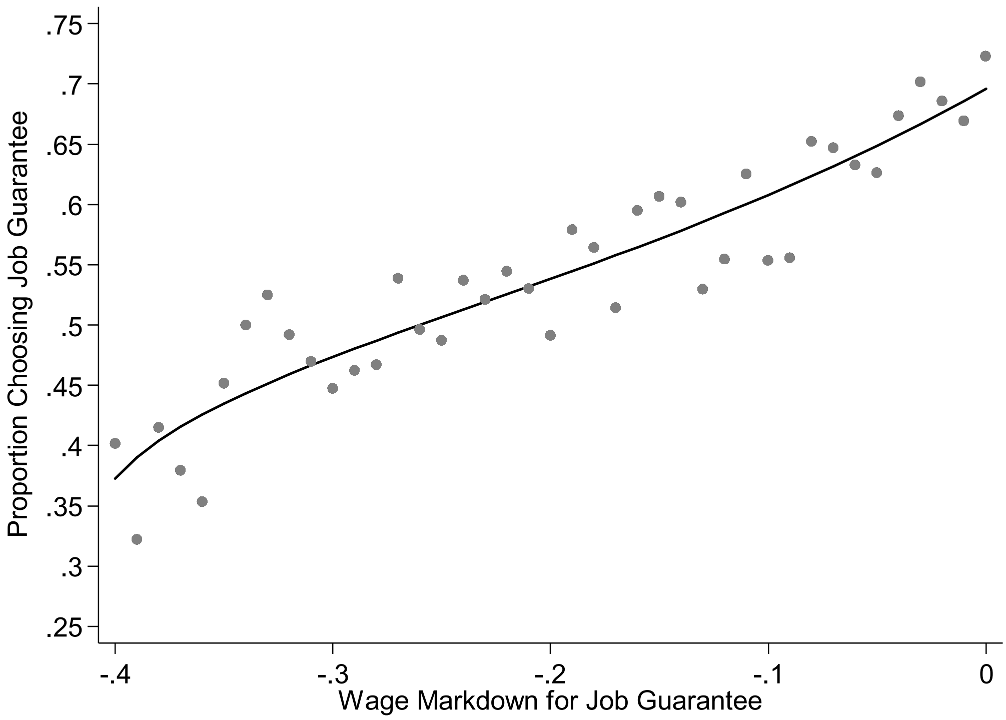
Exhibit 3: Employment and Earnings Losses From C19

	Pr[Employment Loss]					
	Job loss		Zero hours		Not working	
	(1)	(2)	(3)	(4)	(5)	(6)
Job guarantee	-0.050 (0.019)	-0.050 (0.019)	-0.066 (0.011)	-0.061 (0.011)	-0.116 (0.021)	-0.111 (0.021)
Age	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.004 (0.001)	-0.004 (0.001)
Female	0.009 (0.017)	0.011 (0.017)	-0.003 (0.012)	0.000 (0.012)	0.007 (0.019)	0.012 (0.019)
Education≤10th standard	-0.070 (0.019)	-0.072 (0.019)	0.008 (0.013)	0.003 (0.014)	-0.062 (0.021)	-0.070 (0.021)
Informal	-0.013 (0.019)	-0.016 (0.019)	-0.070 (0.015)	-0.071 (0.015)	-0.083 (0.022)	-0.087 (0.021)
Lockdown zone		0.051 (0.016)		-0.026 (0.012)		0.025 (0.018)
Can work from home		-0.099 (0.025)		-0.053 (0.015)		-0.152 (0.028)
City and state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3045	3045	3045	3045	3045	3045

	Earnings Loss (Rs)					
	All		Working		Paid	
	(7)	(8)	(9)	(10)	(11)	(12)
Job guarantee	-984 (193)	-929 (192)	-1120 (250)	-1029 (251)	-442 (454)	-523 (435)
Age	-1 (10)	-1 (10)	2 (13)	3 (13)	61 (33)	64 (34)
Female	-125 (232)	-50 (225)	7 (290)	46 (284)	-610 (339)	-673 (347)
Education≤10th standard	126 (163)	13 (165)	200 (238)	37 (241)	784 (518)	693 (559)
Informal	686 (197)	618 (191)	1146 (302)	997 (292)	1665 (546)	1570 (498)
Pre-lockdown earnings	0.739 (0.087)	0.739 (0.085)	0.648 (0.120)	0.651 (0.117)	0.165 (0.083)	0.166 (0.083)
Lockdown zone		687 (154)		776 (199)		144 (374)
Can work from home		-2544 (412)		-2839 (474)		-701 (630)
City and state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3045	3045	2040	2040	489	489

Notes: Standard errors in parentheses. The city fixed effects are for the biggest 9 cities in terms of population and state fixed effects for Bihar, Jharkhand and Uttar Pradesh.

Exhibit 4: Willingness to Pay for a Job Guarantee



Notes: Based on the sample of 2512 workers who do not have a job guarantee. The median WTP for a job guarantee is determined from a logistic regression of whether an individual chooses the job guarantee on the randomly allocated wage markdown as described in detail in the Appendix. For the logistic model slope in the Figure the median WTP corresponds to a wage markdown of -0.255 (standard error = 0.014), or 25.5 percent of the wage. This comes from the ratio of the estimated constant term ($\beta_G = 0.758$ with associated standard error 0.064) to the coefficient on the wage markdown ($\beta_W = 0.030$ with associated standard error 0.003).

Exhibit 5: Demand for a Job Guarantee

	Choice Experiment		Would Like Job Guarantee		More Likely to Want Job Guarantee Due to Corona Lockdown	
	Median WTP, Proportion of Daily Wage	Median WTP, Daily Rs	Proportion	Gap (Standard Error)	Proportion	Gap (Standard Error)
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.255 (0.014)	81	0.768		0.369	
Age≤25	0.302 (0.031)	93	0.782	0.023 (0.017)	0.376	0.012 (0.020)
Age>25	0.234 (0.015)	76	0.759		0.364	
Female	0.354 (0.046)	86	0.798	0.042 (0.018)	0.444	0.104 (0.022)
Male	0.229 (0.014)	79	0.756		0.340	
Education≤10^{th} standard	0.257 (0.015)	78	0.790	0.083 (0.020)	0.393	0.089 (0.021)
Education>10^{th} standard	0.250 (0.036)	90	0.707		0.304	
Informal	0.247 (0.014)	75	0.788	0.084 (0.021)	0.405	0.152 (0.021)
Employee	0.297 (0.042)	109	0.704		0.253	

Notes: Standard errors in parentheses. Based on the sample of 2512 workers who do not have a job guarantee.

Online Appendix

Table A1: Survey Sample, Definitions and Questions

Sample Selection. The survey interviewed 5525 individuals, who had work at some point in the previous ten years. Of them, 3045 were employees or informal workers, as defined below. About 43 percent of all surveyed workers were self-employed or worked in their family business before the pandemic (February 2020). Another 1.5 percent were government employees. As the focus of interest of this paper is on a job guarantee, these self-employed individuals and government workers are excluded because they (effectively) have a job guarantee through their business or the government. A very small number of individuals (0.3 percent) were unemployed for a duration dating back to well before the lockdown. They are also excluded from the analysis because of the focus on changes in labour market outcomes for those in work before the pandemic.

Employees. Employed by private for-profit company or proprietorship or partnership or employed by co-operative societies/trust/other non-profit institutions.

Informal Workers. Employed casually (e.g. daily labourer, casual farm worker) or employed by private households (e.g. maid, watchman, cook, etc) or employed by a single individual.

Big Cities. Indicators for Class I cities, which are defined by Census 2011 as urban agglomerations that had a population of 100,000 or more in the census.

Unable to Work from Home. Indicator for those who could not do any work from home (in their pre-Covid employment), based on the following question:
Some workers, such as website designers, can easily perform many of their work duties from home. Others, like clothes shop attendants, cannot do much work from home. Thinking of your current job, what percentage of your work duties could be done working from home? 0% from home/…../100% from home.

Choice Experiment
From Hindi translation to English, the enumerator's screen appears as follows:

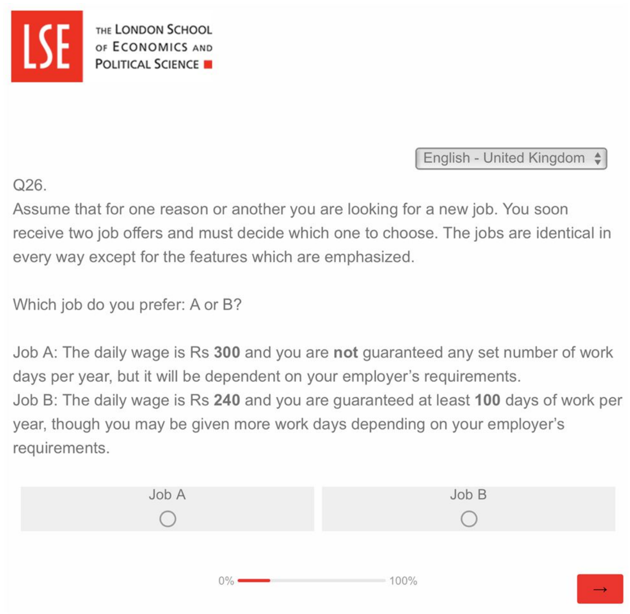


Table A2: Employment and Earnings Losses From C19, Plus Industry and Firm Size

	Pr[Employment Loss]					
	Job loss		Zero hours		Not working	
	(1)	(2)	(3)	(4)	(5)	(6)
Job guarantee	-0.044 (0.020)	-0.040 (0.020)	-0.082 (0.012)	-0.077 (0.012)	-0.123 (0.022)	-0.117 (0.022)
Age	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.004 (0.001)	-0.004 (0.001)
Female	-0.018 (0.018)	-0.018 (0.018)	-0.001 (0.012)	0.001 (0.012)	-0.018 (0.020)	-0.017 (0.020)
Education≤10th standard	-0.039 (0.020)	-0.046 (0.021)	0.004 (0.014)	0.000 (0.014)	-0.035 (0.022)	-0.041 (0.022)
Informal	-0.003 (0.023)	-0.006 (0.023)	-0.042 (0.018)	-0.043 (0.018)	-0.045 (0.026)	-0.049 (0.026)
Lockdown zone		0.050 (0.017)		-0.022 (0.012)		0.028 (0.018)
Can work from home		-0.111 (0.026)		-0.043 (0.015)		-0.154 (0.029)
City and state fixed effects	Yes	Yes	Yes	Yes	Ye	Yes
Industry and firm size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3045	3045	3045	3045	3045	3045

	Earnings Loss (Rs)					
	All		Working		Paid	
	(7)	(8)	(9)	(10)	(11)	(12)
Job guarantee	-975 (200)	-914 (202)	-1214 (262)	-1001 (267)	-829 (510)	-870 (499)
Age	5 (10)	5 (10)	12 (13)	10 (13)	59 (31)	63 (31)
Female	248 (221)	255 (219)	489 (288)	443 (287)	51 (377)	3 (388)
Education≤10th standard	51 (170)	-28 (171)	77 (250)	-29 (250)	508 (519)	442 (530)
Informal	355 (215)	296 (211)	813 (314)	719 (306)	2194 (827)	2111 (793)
Pre-lockdown earnings	0.739 (0.090)	0.741 (0.088)	0.646 (0.124)	0.680 (0.199)	0.170 (0.083)	0.169 (0.083)
Lockdown zone		658 (155)		648 (121)		-10 (394)
Can work from home		-2416 (412)		-2681 (121)		-574 (598)
City and state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry and firm size fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3045	3045	2040	2040	4894	489

Notes: Standard errors in parentheses. The city fixed effects are for the biggest 9 cities in terms of population and state fixed effects for Bihar, Jharkhand and Uttar Pradesh. The industry and firm size fixed effects comprise 20 industries and 6 firm size groupings respectively.

Table A3: Randomisation Tests for Choice Experiment

	p-value of F-statistic testing joint significance of wage gap dummy variables
Age≤25	0.53
Female	0.05
Education≤10th standard	0.16
Informal	0.38
Big city	0.30
Bihar	0.65
Jharkhand	0.77
Uttar Pradesh	0.61
Sample size	2512

Table A4: Reasons Given For Not Wanting a Job Guarantee

	All	Informal	Employee
Do not need it	0.564	0.607	0.564
Domestic commitments	0.241	0.244	0.235
Want to do other types of work	0.164	0.160	0.173
Student	0.046	0.022	0.101
Ill or disabled	0.017	0.017	0.017
Sample size	584	405	179

Table A5: Regressions For Outcomes Considered in Exhibit 5

	Pr[Choose Job Guarantee]	Pr[Would Like Job Guarantee]	Pr[More Likely To Want Job Guarantee Under Corona Lockdown]
	(1)	(2)	(3)
Age	-0.005 (0.001)	-0.004 (0.001)	-0.002 (0.001)
Female	0.053 (0.021)	0.061 (0.019)	0.141 (0.022)
Education≤10th standard	0.043 (0.024)	0.063 (0.022)	0.046 (0.023)
Informal	0.010 (0.024)	0.071 (0.023)	0.145 (0.023)
Wage markdown	-0.773 (0.078)		
City and state fixed effects	Yes	Yes	Yes
Sample size	2512	2512	2512

Notes: Standard errors in parentheses.

Theory and Empirical Specification

Following the literature on random utility models, jobs are characterized by various attributes a that take on values X_{aj} for job $j \in \{\text{A,B}\}$. Individual i receives the following utility from job j: $U_{ij} = u(X_{ij}) + \varepsilon_{ij}$, where $u(X_{ij}) = \sum_a \beta_a X_{aij}$ and ε_{ij} are idiosyncratic taste terms which are assumed to be iid, independent of attributes X and drawn from a type I extreme value distribution. If the underlying preference parameters β are estimated with observational job choice data, there would be concerns over the independence assumption being violated when unobserved job attributes are correlated with included job attributes like wages. The experimental design accounts for this in two ways. First, the focus is on just two job attributes varying across the two jobs – a job guarantee and the daily wage rate, holding all else constant. Second, of the two attributes under consideration, the wage difference across the two jobs is randomly assigned by the experiment. It therefore avoids the problem of being an equilibrium wage-guarantee profile, where the former is likely to be correlated with unobserved tastes for the job which would bias the estimated parameters.

Each individual participating in the survey was asked to consider a situation in which he/she must choose between one of two job offers, which are identical in every way except for the features which are emphasized - wages and job guarantee. This reduces the attribute space over which decisions are being made into one dimension – a trade-off between having a job guarantee G and the wage markdown M. Job A pays the person his/her usual daily wage W (in Indian Rupees). It does not guarantee any set number of work days per year ($G = 0$). Job B is identical in every way, except it pays the worker a daily wage of $(1 - M_i/100)W$ (in Indian Rupees) and guarantees at least 100 days of work per year ($G = 1$).

Then the log odds of choosing job B which offers a job guarantee relative to job A which does not is: $\ln(q_{iB}/q_{iA}) = \beta_G + \beta_W \ln(1 - M_i/100) \approx \beta_G - \beta_W(M_i/100)$. Unlike observed job choice data, the experiment randomly assigns M_i so that any concerns over unobservables being correlated with it are minimised. Individuals were randomized into different values of M_i drawn from $\{0, 1, 2, \ldots, 39, 40\}$. Table A3 in the Appendix shows that the randomised markdowns turn out uncorrelated with key demographic and employment characteristics that might otherwise be expected to vary systematically with them.

The underlying preference parameters β_G and β_W can be estimated from a logistic regression of an indicator for choosing Job B on the markdown M_i that is randomly assigned. β_G is the marginal change in the log odds of choosing a job guarantee for an assigned wage cut. The willingness to pay for a job guarantee is then given by $WTP \equiv M/100 \approx \beta_G/\beta_W$. Having estimated the preference parameters, the median willingness to pay in Rupees can be computed at the median usual daily wage rate as $(\beta_G/\beta_W) \times W$. The first row of Exhibit 5 reports these numbers in columns (1) and (2) respectively. Subsequent rows estimate the parameters for the specific groups under consideration and evaluate the median WTP at the median usual daily wage rate of each group.