The Crisis and Job Guarantees in Urban India

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August 2021

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Abstract

This paper uses a new field survey 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 as they were not hit so hard in terms of the increased incidence of job loss or working zero hours and in experiencing earnings losses. A stated choice experiment reveals evidence that low-wage workers are on average willing to give up around a quarter of their daily wage for a job guarantee, with higher valuations for young and female workers. Direct survey questions corroborate the demand for an urban job guarantee, with informal, female and low-education workers being most likely to want a job guarantee, and to want it more due to the crisis. The latter is reconfirmed by looking at experimental variations in willingness to pay in the reasons why workers state they would like a job guarantee.

Keywords: job guarantee, India, urban labour markets, job choice experiment, Covid-19
JEL codes: J46, J68, L52, P25

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Acknowledgements

We thank Shania Bhalotia, Pranav Chaudhary, Maitreesh Ghatak and Fjolla Kondirolli for excellent suggestions and comments. Financial support from the ESRC and from the ERC Starting Grant 760037 is gratefully acknowledged. The primary survey was reviewed and approved by the LSE Research Ethics Committee (REC Ref. 1129).

1. Introduction

Job guarantees 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". This paper evaluates and quantifies the value of a job guarantee to workers in this setting.

The ILO has pointed to the risks faced by informal workers in developing economies, many of whom have been directly affected and others whose jobs are at greater risk due to lockdowns (ILO, 2020a).[2] Informal work, including casual, 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). A number of relief packages have been put forward for informal workers under Covid-19 (Gentilini et al., 2021),[3] and international organisations, such as the OECD and the ILO, have explicitly called for job guarantees to prevent a permanent deterioration in work and living standards (OECD, 2020; ILO, 2020b).

Covid-19 is expected to push 120 million people into poverty, earning less than \$1.90 a day, with a concentration in urban areas.[4] Many of these individuals were not ultra-poor before the pandemic and therefore in the crisis have fallen outside traditional social assistance and poverty alleviation programmes. This makes it harder to reach them and to provide social protection during an emergency (Gerard et al., 2020). In response to the livelihood crisis, several countries have quickly enacted

[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
[3] New and expanded job guarantee programmes have been put in place in various countries, including Armenia, Azerbaijan, Bhutan, Cambodia, Ethiopia, Grenada, Guam, Guinea, Hong Kong, India, Indonesia, Kazakhstan, Kenya, Korea, Madagascar, Mexico, Myanmar, Nepal, Nigeria, Palau, Philippines, Rwanda, St Lucia, St Vincent and Grenadines, Taiwan, Uganda, Uzbekistan, West Bank and Gaza, and Zimbabwe.
[4] https://blogs.worldbank.org/opendata/updated-estimates-impact-covid-19-global-poverty-looking-back-2020-and-outlook-2021

employment programmes, such as Covid-safe extensions to South Africa's Expanded Public Works Programme. Job guarantees have the scope to help informal workers recover from the pandemic. Their self-targeting feature can be effective in identifying individuals who have lost their livelihoods and are new entrants into poverty and welfare systems (see Besley and Coate, 1992).

India typifies concerns over urban labour markets in developing economies. While agriculture and rural works have provided some respite in village economies during the crisis (e.g. Afridi et al., 2021), low-income individuals working in urban areas of developing economies have seen little assistance. Even before the pandemic, urban poverty rates had started to catch up with the much higher poverty rates in rural India (Datt et al., 2020). Labour force participation rates were low (57 percent for men and 16 percent for women) and the majority of the workforce is informal.[5] Regular wage/salaried employees make up less than half of the urban workforce, and the rest do their jobs in a hinterland of casual work and outsourced contracts. Even among regular employees, over 70 percent have no 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.

Like other developing economies, India has a young workforce - 68 percent of the urban workforce is 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 the first wave of Covid-19 (Hale et al., 2020). It came into effect on March 24, 2020 and lasted till at least mid-May.

[5] Periodic Labour Force Survey PLFS microdata, 2017-18.

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 (Bhatiya et al., 2021). The urban unemployment rate rose about 12 percentage points year-on-year during the lockdown months of April to June 2020 (NSO 2021) and GDP fell by 23.9 percent. These big disruptions have continued to be felt widely, and the second wave of the pandemic has intensified the debate over actual impacts and recovery policies to address the continuing livelihood crisis in urban areas. Although a key challenge for the future, little is known of the efficacy of different labour market policies to recover from the pandemic. Regular data collection has suffered due to the pandemic and much of the early analysis 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 and policies for 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 the 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 accords well with recent work on the labour market impacts of the pandemic in developed economies where workers were hit hard (Adams-Prassl et al., 2020; Blundell and Machin, 2020; Coibion et al., 2020). But the scale of the hit to Indian workers is an order of magnitude bigger. About a quarter of workers lost their jobs, another 9 percent 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 a credible active labour market policy that could assist economic recovery in urban areas (see Dreze 2020, State of Working

India 2021 for policy proposals and actual state programmes). India already runs the world's largest job guarantee programme under its Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), which entitles rural households to demand 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 subsequently indicated plans for an urban job guarantee in small towns and cities to address the crisis, but no new policy is yet in place (NDTV, 2020). Proposals to operationalise employment opportunities in urban areas 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, 2019a), but there is a dearth of knowledge on this aspect of labour market policy in urban labour markets which have much more varied skill levels and lack the tight community ties of agrarian economies. The survey studied here was specifically designed to examine how the employment and earnings impacts of the lockdown differed by the presence of a job guarantee 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 mediated for workers who had a job guarantee before the crisis. They were relatively shielded by not being hit so hard in terms of the increased incidence of unemployment or working zero hours and in experiencing 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 guarantee. The experiment builds on prior research where there is a long tradition of eliciting preferences for non-pecuniary attributes through surveys in some areas (especially environmental, development and in labour economics). 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; Wiswall and Zafar, 2018; also Mahmud et al. 2021; Lagakos et al. 2020; Imbert and Papp 2020 in developing country contexts).

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 on average willing to give up around a quarter of their daily wage for a job guarantee, with higher valuations for young and female workers. And other survey questions corroborate this significant valuation, with informal, female and low-education workers being most likely to want a job guarantee, and to want it more due to the current crisis. Compared to the job guarantee valuation for conventional economic reasons, there is an incremental increase in willingness to pay due to coronavirus and lockdown. This emerges from study of experimental variations in willingness to pay in the reasons why workers state they would like a job guarantee. The crisis from C19 has therefore acted to reinforce and strengthen the protective value of a job guarantee, both by expanding the set of workers who would like a job guarantee and by an incremental valuation increase.

2. Survey Design and Data Description

Survey Design

The survey took place 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 with 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). Information on wards is available from the

Census of India 2011. Within each cluster of wards, 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 35 individuals per ward cluster were therefore interviewed by survey enumerators on the phone. Due to low labour force participation rates in these areas, individuals with employment at some point in the past ten years were interviewed. This ensured a well-defined wage rate for all participants and minimised concerns over changes in labour force participation from education. Women were over-sampled from the lists due to their low labour force participation rates. Gender-weighted statistics are reported throughout the paper to account for this over-sampling of women. The weights are constructed from the Periodic Labour Force Survey for the comparable sample of individuals who were employees or casual workers in the three states in January to March 2020. This takes the share of women in the sample from an unweighted 28.4 percent to a weighted 10.6 percent.[6]

The survey instrument was developed in English and translated into Hindi by a large professional survey company. The translation was revised by three different native speakers from the surveyed states to adapt to local dialects. Local enumerators completed the surveys a number of times each to ensure questions were easy to understand and appropriate changes were made according to their suggestions. The survey was primarily administered in Hindi by trained enumerators. (English translations were available if needed, but almost none opted for it).

A qualitative pilot was conducted before the field survey on a panel of 50 respondents held by the professional survey company in India, and they were incentivised to point out questions that were difficult to follow. The response was overwhelmingly positive and a field pilot followed. It was conducted with a sample of 150 individuals in the surveyed urban wards whose responses were checked manually for consistency and who were requested to provide detailed suggestions. With the instrument

[6] Results throughout the paper are qualitatively similar when the gender-weighting is not applied or when other waves of the PLFS are used to construct the weights instead (these are omitted for brevity, but are available on request).

fine-tuned in these ways, the survey was administered by local enumerators to the random sample of individuals.

Non-response was low, as just 190 individuals who were contacted refused to participate. This is similar to the low refusal rates (albeit for resurveying), of under 5 percent, reported in urban phone surveys of Abebe et al. (2016). Another 131 individuals were dropped because they either did not complete the survey or provided inconsistent answers. Netting out the non-responses and the inconsistent responses, the survey covered 5,525 individuals. The key reasons for high response rates include local enumerators, references for the survey team from local businesses selling essential items, off-work period for participants due to lockdown restrictions and policy-relevant questions designed to speak directly to their economic distress.

Study Sample

The survey collected information on employment status and earnings of employed individuals. 42.5 percent of the 5,525 surveyed workers were self-employed or worked in their family business before the pandemic (January-February 2020). Another 1.6 percent were government employees. As the focus 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 public sector. A very small number of individuals (1.1 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 the labour force before the pandemic.

The study sample thus comprises 3,029 employees or casual (daily and non-daily informal) individuals who were in work before the first lockdown. They form the relevant group for studying Covid-19 impacts and job guarantees. Just over a third were employees in private businesses while the rest were casual workers including those in public or other types of casual works (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). A distinction between daily and non-daily casual workers is adopted because official labour force statistics record earnings by daily payment status of casual workers. To be precise, *Employees* are defined as individuals who were employed by a private for-profit company or proprietorship or partnership or employed by co-operative societies/trust/other non-profit institutions in their pre-Covid job (or the current job if it is the same as their last pre-Covid job). *Daily* workers are defined as workers who are employed casually in their pre-Covid job and who are paid daily wages for their work (e.g. daily labourer, casual farm worker). *Informal* workers are defined as workers who are employed casually and who are not paid daily (e.g. maid, 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), but is tailored to urban India including questions drawn from the National Sample Survey Office and the Periodic Labour Force Survey of India. 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, administrative data 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 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 (2019) 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.

Job Guarantees

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 a 40 percent markdown. (See Appendix Table A1 for definitional details, including a visual representation of the job vignettes, as it appears on enumerators' screens translated into English).

3. Labour Market Outcomes During 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?

Table 1 presents statistics on the shares of workers that have a job guarantee in work prior to the crisis broken down by various demographic and job characteristics. Just over 16 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 (24.2 percent) than daily and informal workers (17.2 percent and 11.1 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 informally employed. The job guarantees are primarily provided by employers (31.6 percent) and job contractors or temporary agencies (35 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 national rural job guarantee.

Table 1 also shows that urban areas which continued to see a partial or complete lockdown, after the strict national lockdown ended on 3rd May 2020, 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. 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?

Table 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 (following the definition used in the PLFS). 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 32.7 percent.

Panel B of Table 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 anything despite having a job. Panel C shows that those who continued to be “in work” saw a slightly smaller – 80 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 relatively protected from both job and earning losses. Even though workers without a job guarantee had higher earnings before the pandemic, they were about 13.9 percentage points more likely to be out of work, either through job losses or through zero hours at work (7.7. and 6.2 percentage points higher respectively). They suffered much greater earning losses – over Rs 7,400 monthly or 87 percent of average pre-Covid earnings, compared with Rs 5,900 monthly or 74 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 68 percent for workers who had a job guarantee and 26 percent compared to 15 percent for those who got paid. While these findings do not provide causal evidence that the presence of job guarantees protected these workers, they are consistent with smaller losses for those in jobs with a guarantee of work, an issue which is explored more systematically next.

Statistical estimates

Table 3 presents a more systematic analysis of differences in employment and earnings losses for those with and without a guarantee of work in their jobs before C19. For worker i, the change in employment and earnings 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) 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 indicators for daily and 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, location fixed effects are included to account for time-invariant differences across locations. In particular, ward clusters in big cities are assigned to their individual city fixed effects while wards in smaller towns are assigned to their state fixed effects, as they have fewer observations per town. For example, Patna, the capital city of Bihar, takes its own indicator while Araria, a smaller town in Bihar, is assigned to a Bihar indicator. All three states have some smaller towns.

Table 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 Table 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). The probability of job loss is a sizable 9.4 percentage points lower for workers who have a job guarantee before the pandemic. Their chances of being on zero hours are also lower by 7.5 percentage points and of not working by 16.8 percentage points. Workers without a job guarantee experienced much bigger earning losses, with the full sample losing between Rs 1074 and Rs 1111 (specifications (7) and (8)) on average. The earning loss protection for workers with 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 showing how the lockdown variables themselves impact on employment and earnings, and how their inclusion affects the estimated coefficients on the demographics. Table 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, except for earnings losses within the group with some pay. Daily and informal workers do better on employment, but they take a big hit on earnings.

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 for workers with a job guarantee remains robust to their inclusion. Additional lockdown-related variables, namely industry and firm size, were also included to account for differences in lockdown restrictions across industries and labour law differences across firms (Table A2 in the Appendix). Their inclusion does not alter any of the key results. The job guarantee results remain intact and highly similar in magnitudes.

4. The Value of a Job Guarantee

The previous section presented strong and robust evidence that workers who lacked a job guarantee before the C19 pandemic experienced larger employment and earning losses on lockdown. The pandemic has led to the largest economic contraction in India since independence and the economy is taking time to recover. There are concerns that many workers will continue to face economic hardship, especially in sectors that remained more shut down, and that in the absence of a policy response will be placed on a trajectory heading towards long term worklessness.[7] New policies, primarily an urban job guarantee, are therefore being considered at local, state and central levels to prevent a new set of young 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, Maestas et al. 2018). It is particularly suited to valuation of a job guarantee, which is a well-defined job attribute that people understand in India.

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

[7] The survey also asked about expectations in the next three months. Respondents showed a large degree of pessimism overall, as about 80 percent of workers expected to lose their current job, be working for fewer hours or 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 -- 71 percent expected worse outcomes as compared to 81 percent amongst those without a job guarantee. These worries have been largely realised even before the second wave of the pandemic. Having re-contacted a subset of respondents, new survey evidence from January to March 2021 shows that 40 percent of workers continued to be out of work (in the week before the survey) or without pay (in 2021), ten months on from the first lockdown of April to June 2020 (when the equivalent figure was 80 percent) (Dhingra and Kondirolli, 2021).

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 in [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 (i.e. Rs 300 × (1 – 20/100)).

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 would be biased if omitted non-pecuniary benefits and costs 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 the exposition presented in the Appendix).

Figure 1 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 (2,514 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. (Table 4 contains randomisation tests by key demographic characteristics, which show that the markdown in the experiment is uncorrelated with them). 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 urban workers in India 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 Appendix exposition). For all workers without a job guarantee, the median willingness to pay is estimated to be 25.7 percent, showing that workers are willing to take a fairly sizable wage cut for a guarantee of 100 days of work.

To put this number in context, the State of Working India (2019) estimates a total bill of Rs 4.5 billion and a wage bill of Rs 2.7 billion to cover 100-150 days of work at Rs 500 per day for 52 million workers in their proposed urban job guarantee. This job guarantee would therefore need to create additional value of 0.66 per unit spent on wages for a benevolent government (that maximises worker welfare) to break even on the programme. When the value placed by workers on a job guarantee is accounted for, the additional value generation needs to be 0.4 ceteris paribus. Of course, creation of urban assets and amenities and other general equilibrium considerations (e.g. Muralidharan et al. 2020) could well justify these costs, but implementation in urban areas could be a tall order due to administration and governance difficulties such as those encountered in previous job guarantee policies (Ravallion 2019b).

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

Table 5 systematises the WTP analysis further, together with other estimates of demand for a job guarantee from non-experimental questions asked in the survey. Columns (1) and (2) show the estimated willingness to pay for a job guarantee as a proportion of the wage and in Rupees for different groups of workers. As already noted in the discussion of Figure 1, the median willingness to pay for a job guarantee is 25.7 percent of usual wages across all workers. This corresponds to Rs 87 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 – 79.7 percent of workers without a job guarantee say they would like a guarantee of at least 100 days of work in the year in the non-experimental question. 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, because take up can vary and thereby generate differences in valuations.[8] Table 5 examines these variations in the WTP for a job guarantee. It shows younger workers and female workers have a higher willingness to pay. The responses to the non-experimental survey questions also show female workers to be more likely to want a job guarantee and want a job guarantee more in the crisis. Low and high education workers have similar WTP, but low education workers are more likely to want a job guarantee. Similarly, daily and informal workers are much more likely to say they would like a job guarantee, but the amount that employees are willing to pay is higher. Importantly, casual and low-education workers have become much more likely to want a job guarantee due to the pandemic. Daily and informal workers are 26.5 and 10.2 percentage points more likely than employees and low education workers are 8.5 percentage points more likely than higher education workers to want a job guarantee due to the pandemic.[9]

5. Implications and Further Analysis

This section discusses implications of the findings for understanding the reasons and extent to which workers value a job guarantee and, in doing so, pushes the analysis further to study mechanisms

[8] Because the wage 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. The slope from a linear regression of job guarantee choice on the wage markdown is -0.824 (with a standard error of 0.056). This just moves slightly to -0.816 (with a standard error of 0.055) when the demographic variables are included, all of which are insignificant as shown in column (1) of Table A3 in the Appendix.

[9] 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 are given in Appendix Table A3.

and to extend variations in willingness to pay by reasons workers say they want or do not want a job guarantee. Generating an understanding of the reasons why workers want or do not want a job guarantee and how this shapes their valuation of a guarantee is important for the design of active labour market policies in urban labour markets. The issues are explored by looking at the role of different channels for worker valuation that have been suggested in the literature and by examining responses and reasons together with heterogeneity in willingness to pay for workers who do or do not want a job guarantee. Additionally, results from alternative samples and a comparison with nationally representative surveys are also presented.

Why do workers value a job guarantee?

One classic reasoning as to why workers value job guarantees is that they help risk-averse workers overcome seasonality, work fluctuations and uncertainty in income by guaranteeing a set number of work-days (see Ray 1998, Chapter 13 for a textbook analysis of casual work). To study a possible role for risk aversion, the survey instrument included a set of questions to elicit risk preferences of participants. This risk measure was collected for a subset of respondents who were administered an additional risk aversion experiment that builds on the one used in Falk et al. (2018). It was conducted on a subset to keep the general questionnaire short to avoid survey fatigue, and comprises of a set of five questions, which asks respondents to choose between a lottery and a sure payment that varies across the five questions in a step-ladder way. See Figure A1 of the Appendix for the extensive form structure of the experiment.

The first question offers a sure payment of Rs 1,600 and a draw that has equal chances of giving Rs 3,000 or nothing.[10] If the respondent chooses the draw, then the sure payment is increased to Rs 2,400 while the sure payment is reduced to Rs 800 if the sure payment is chosen in the first question. Based on the second set of answers, the sure payment is again increased or decreased in each case by Rs 400. The third set of answers is altered by Rs 200 and the fourth set by Rs 100, until the amount of

[10] We closely follow the Hindi translation of Falk et al. (2018) but refine it to reflect local dialect. We also start with Rs 1,600 (or 0.6 per cent of mean urban annual salary in Bihar, Jharkhand and Uttar Pradesh, taken from PLFS April-June 2018 and inflation-adjusted using CPI(IW)). This compares well with their original experiment in the United Kingdom where the initial value of £160 was roughly 0.6 per cent of mean personal income in 2012.

the sure payment in the final stage goes to Rs 3,100 at most and Rs 100 at least. This produces 32 risk categories of the lowest sure payment at which the worker makes a switch to a draw. Low values of the sure payment mean individuals are more risk-averse as they are less likely to choose a draw even when they are being offered small sums under the sure payment. The experiment confirms that the sample distribution of the chosen sure payment is very left-skewed, implying individuals are mostly risk averse in that they prefer a sure payment that is below the expected value from the draw (Rs 1,500).[11]

The scope for risk aversion to be a factor at play in why workers value a job guarantee was explored using this risk preference measure in two ways. First, the extent to which risk aversion is correlated with choosing the job guarantee in the choice experiment and in the direct non-experimental survey questions was explored. Panel A of Table 6 shows the results from this exercise where the lowest chosen sure payment value (which is an inverse measure of risk aversion) was included in the experimental and non-experimental job guarantee specifications. It does not uncover systematic differences in takeup by risk aversion, but does show a slight uptick in the proportion of workers who have become more likely to want a job guarantee due to the crisis. Evaluated at the mean sure payment value of Rs 700, this rise in takeup by risk aversion however proves to be economically small in magnitude (less than 2 percent). The second means of studying risk aversion comes from looking at variations in willingness to pay in the job choice experiment. Workers who are not risk averse (those who choose sure payments of over Rs 1,500) have a modestly smaller willingness to pay at 24.3 percent of their daily wage or Rs 84, as compared to 25.8 percent of their daily wage or Rs 87 for risk averse individuals.

Moving beyond risk aversion, another standard reason for wanting a job guarantee is that it provides higher expected utility by raising the probability of getting work. Under this reasoning, job guarantees are desirable because they raise the first moment (expected income) for those who do not otherwise expect to have adequate livelihoods. It therefore provides income support through work, as

[11] Distribution of the risk measure in the survey is extremely similar to that in Falk et al. (2018) for the three states of Bihar, Jharkhand and Uttar Pradesh whose individual data is available at https://www.briq-institute.org/global-preferences/downloads?submitted=1.

in workfare models of job guarantee (Besley and Coate, 1992). This parallels the literature on economic policy uncertainty which explores the relationship between aggregate output and the first and second moments of policy shocks (Baker et al., 2016).

To examine this empirically, Panel B of Table 6 reports results from including an indicator of whether the individual had work for just a part of the previous year into the experimental and non-experimental regressions. The included variable is derived from the same question as that in the Employment-Unemployment Survey of the National Sample Survey Organisation of India, but the response options are finer to account for worklessness during the lockdown months. A full-year is categorised as 40 weeks or more (as the lockdown duration amounted to less than twelve weeks till the end of the survey period). Individuals who lacked a full year's work are 5.3 percentage points more likely to choose a job guarantee in the experimental question and 8.4 percentage points more likely to want a job guarantee in the direct survey question. They are also slightly more likely to have an increased demand for a job guarantee due to the pandemic. These differences in job guarantee preferences are also examined through the willingness to pay for workers with and without a full year's work. Workers who lacked a full year's work place a higher valuation on a job guarantee. Their WTP is 27.4 percent of their daily wage, or Rs 89 per day.

The finding of a greater desire for a job guarantee for less than full-year workers – those that could be considered as having lower labour market attachment - is consistent with an interpretation of the value of a job guarantee in terms of expected workdays gained which can be connected to expectations over honouring of the job guarantee (see Appendix for a formal description in terms of expected workdays). This is important since some research has highlighted that job guarantees need not be honoured and India's MGNREGA suffers from job rationing (Dutta et al., 2021). For the three poorer states studied in this paper, the probability of getting work under MGNREGA is estimated to be in the range of 21.5 to 46.4 percent (compared to the all-India probability of 55.6 percent). Interpreting the willingness to pay as the expected additional days of work that a job guarantee provides, the range of WTP estimates is 23 to 31 percent across different specifications in Table 5, which is within the observed range of the probability of getting work under the rural job guarantee programme in these states.[12]

Another reason for job guarantees could be that they motivate workers to not shirk at work. For example, in the canonical model of Ray (1998), workers prefer permanent contracts because they provide higher wages, which in turn motivates workers to exert more effort to hold on to the high-wage work. This reasoning is unlikely to apply to the setting of job guarantees because the observational data suggest that jobs with a guarantee pay lower wages (on average). Further, the job vignettes choice experiment is designed to control this, as it holds all other job attributes fixed. This is discussed in the light of further evidence on take-up rates below.

Why do some workers not choose nor want a job guarantee?

Since the survey was conducted on the entire relevant population of individuals in work, then it should come as no surprise that some workers do not choose nor want a job guarantee. There are a variety of possible reasons why, like reduced wages, existence of a stigma associated with guarantees or not wanting to work up to the hundred days of work the guarantee ensures. In fact, out of the 2514 workers without a job guarantee, 20.4 percent said they would not want a job guarantee.

Table 7 summarises the main reasons given by these workers for not wanting a job guarantee in their current or previous job. A majority (61.7 percent) said they do not need it. A further 21.4 percent (mostly females) reported having domestic commitments that prevent them from taking one, whilst 18.4 percent stated they would want to do other types of work. The small remainder were students (4.8 percent) or reported being ill or disabled and therefore unable to take one (1.1 percent).

There are variations in these reasons for not wanting a guarantee by type of worker, as shown in the other three columns of Table 7. Daily workers, who do not want a job guarantee, are more likely to want to do other types of work (39.2 percent v 17.5 percent for employees) and less likely to be students (3.2 percent v 10.4 percent for employees). With more women being informally employed,

[12] The range is calculated as one minus the rationing rates for Bihar, Jharkhand and Uttar Pradesh from Dutta et al. (2021).

informal workers are also more likely to not want a job guarantee due to domestic commitments (27.8 percent v 18 percent for employees).

That some people simply do not want a job guarantee is additionally confirmed by the fact that in the job choice experiment a minority of workers who do not have a job guarantee would not choose one even at a zero wage markdown. Closer scrutiny of Figure 1 shows that, whilst a sizable majority over three-quarters do, the remainder would not choose the job with a guarantee even when the wage is not altered from the reference wage in their job. Delving deeper reveals two main reasons for this. First, as already noted, there are some workers who point blank do not want a job guarantee and these form a significant number of this group not choosing the guarantee at no markdown. Second, there are some workers who would only want a job guarantee because of the pandemic.

The first group of these clearly has reasons why they would not want a job guarantee at the same wage. Two thirds of them say they do not want one in their current or previous job because they say they do not need it, with the bulk of the others having domestic commitments that prevent them from working more. These workers are therefore consistently choosing to opt out of a guarantee, suggesting that they attach a perceived stigma or disutility (or both) to having one. For the second group who do not choose the job guarantee position when there is no markdown, all but one of these workers say that the pandemic and related lockdowns is the only reason for wanting a guarantee in their work.[13] Put differently, were it not for the crisis they would be in the do not want a job guarantee group.

These patterns imply that looking at willingness to pay by reason for wanting (or not wanting) a job guarantee could be important. Indeed, it turns out to be. The columns of Table 8 show results that separate workers who would like a job guarantee by the reason they would like it. These are economic reasons only, coronavirus reasons only and both economic and coronavirus reasons. Considering first responses on whether there are differences in choosing the job with the guarantee in the choice experiment, the first two rows show the proportion that choose the job at all wage markdowns (0 to 40 percent inclusive) and only at the 0 percent markdown. The pattern for all wage markdowns shows

[13] The one worker who differs says that there is not enough work.

differences in job guarantee take up by reason, with 70 percent choice if both economic and C19 reasons underpin their wanting a job guarantee, 64 percent if only economic reasons were stated and a smaller 45 percent for only pandemic reasons.

At zero wage markdown, the take up rates are close to full with economic reasons for wanting a job guarantee – at 97 percent for economic reasons only and 90 percent for both economic and C19 reasons. It is a lot lower at 58.1 percent for C19 reasons only. Therefore, not surprisingly, it is this latter group, those who say they would like a job guarantee for C19 reasons, who report a much higher proportion of wanting a guarantee more because of the crisis (at 68 percent).

What about different valuations of a job guarantee? These also turn out to vary by reasons for wanting a job guarantee and whether individuals would like one. The first thing to notice is that mean willingness to pay is higher than then the overall mean of 25.7 percent at 33.1 percent (Rs 109) for individuals who would like a guarantee for whatever reason and this is because the group who would not like a guarantee place no value on having a job guarantee.[14] Breaking down by the three mutually exclusive sets of reasons produces a pattern pointing strongly to there being an incremental increase in WTP due to the crisis of about 15 percent. This is the mean WTP for the group wanting a job guarantee for coronavirus reasons only. The same number of 15 percent arises as the mark up on top of the economic reasons only (which is 31 percent) for the group who say that both economic and coronavirus reasons underpin their wanting a job guarantee. This group has a very large 46 percent valuation, which is further evidence pointing to an increased demand for a job guarantee in the crisis.

Finally, it is worth considering whether any of the results might be affected by an inability to comprehend the job vignettes. The detailed gradations just considered seem to make this unlikely to be very important with clear evidence of almost universal take up of the job guarantee position in the experiment when the relevant group one would expect this for (those wanting a job guarantee for economic reasons in non-crisis times) are partialled out. There are two other reasons to be confident here. First, is that the enumerators were highly trained to deliver on explaining clearly what to do in the

[14] The 515 workers who have a job guarantee in their pre-Covid employment also do not value a job guarantee at all.

experiment (this would be more of a pressing worry in online or self-administered surveys, for example). Second, there are very intuitive, systematic patters in the data on the characteristics of who does not want a job guarantee – for example, those on higher wages who have higher shares for not wanting a job guarantee at the same wage rate, largely because they do not want a job guarantee.[15] These higher-wage workers were also more likely to report not needing a job guarantee, suggesting a degree of negative perceptions, such as due to workfare stigma or perceived tie-in associated with the job offering a guarantee of work. This can be easily incorporated into the canonical model of permanent contracts by generalising to negative worker perceptions from stigma or tie-in (or to positive worker perceptions of temporary contracts like from flexibility under gig work). Then workers choosing between a job with or without a guaranteed number of days face a tradeoff between more expected days of work and the cost of stigma or tie-in. They therefore need not choose a job guarantee at the same wage or, depending on the strength of their disutility, even if a compensating differential was on offer with the job guarantee.

How does the survey sample compare with representative labour force surveys?

The survey was conducted by phone due to social distancing restrictions, which raises concerns over exclusion of poorer individuals who lack access to phones. However, phone penetration in urban India is very high, which alleviates some of these exclusion concerns. According to the nationally representative National Family Health Survey NFHS-4, 96.1 percent of urban households in India had a mobile phone in 2015/16. In the three states of Bihar, Jharkhand and Uttar Pradesh, mobile phone penetration was lower but still between 89 to 92 percent (Hathi et al. 2020). These figures refer to all areas in these three states, and urban areas tend to have higher mobile coverage. In fact, subscription rates in urban areas have grown by 11.6 percent over the last five years, according to the Telecom Regulatory Authority of India.[16] The exclusions from a phone survey are therefore present but likely to be smaller than that suggested by existing phone penetration rates. This is particularly the case for the

[15] The average wage of those not choosing the job guarantee is 15 percent higher than those choosing one (under no markdown) for the non-experimental question and 13 percent higher for the job vignettes.
[16] Press release No. 50/2020 and No. 37/2015 for 30th April 2020 and 30th April 2015.

population of interest - younger individuals who were in the labour force before the pandemic. Nonetheless, the phone survey can lead to exclusions at the low end of the income distribution and the analysis is examined further for representativeness.

Comparing with the official Periodic Labour Force Survey, the sample is broadly representative of the distribution in the PLFS for this period (January-March 2020). An exact match is unlikely as the survey periods will not exactly match even when the survey months are broadly the same. The median wage reported in the PLFS of Rs 300 is identical to the median wage in the survey sample, but the mean wage is higher in the PLFS (Rs 405 compared to Rs 339 in the survey). Figure 2 provides a visual representation of the daily wage distributions for the equivalent sample in the PLFS and the survey. It clearly shows that the mean wage differences are driven primarily by the heavier right tail of the wage distribution in the PLFS. While the survey provides comparable coverage of low and middle wage bins, it underrepresents workers with daily wages above the 90th percentile. The top exclusions arise because the survey misses out on very high-income workers, who are less likely to respond to a survey but would be legally obliged to answer the official labour force survey.

The coverage of the survey and its top exclusions can be examined further through correlations between the mean wages for different demographic groups. The demographics are the same as those used in previous Tables, which include young and old, male and female, low education and high education, and big city and small towns. As the PLFS pay data is collected by daily wage status of the worker, this is also incorporated as an indicator into the wage comparison.[17] Across the 32 exhaustive categories of demographics, the correlation between mean PLFS and survey wages is 0.86 for men and 0.77 for women. Noting these differences, the willingness to pay for a job guarantee can be bounded to reflect the exclusion of high income individuals. As an upper bound, if all these individuals had a job guarantee, the estimated WTP would remain the same because they would not be part of the population of interest. If instead all these individuals lacked a job guarantee and they all placed a zero value on having one, then the estimated willingness to pay would change from 25.7 percent to 23.1 percent (=

[17] The survey collected pay information by asking the last pay amount and the number of days worked for that amount. This follows the practice of the Office of National Statistics of the United Kingdom.

25.7 × 0.9 + 0 × 0.1). Although these are extreme assumptions, the estimated WTP is bounded very tightly. Overall, the survey covers a very broad segment of the population in urban areas and the wage patterns are similar to official surveys, albeit with some top exclusions (that are less relevant for the policy issue of job guarantees).

6. Conclusion

This paper examines job guarantees in urban India during the Covid-19 crisis. It begins by using newly collected field data to undertake a before/after lockdown analysis of labour market outcomes. The study shows Indian workers were hit hard during the crisis, experiencing big employment and earnings losses. Importantly, it 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 that occurred.

This protective nature of a job guarantee is quantified 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 just over a quarter of their daily wage to be able to get a guarantee of a minimum days of work. Young 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. Daily casual workers, low-education workers and female workers are more likely to want a job guarantee, and to want it even more due to the current crisis.

Probing further the variation in desire for a job guarantee and in willingness to pay, it is important to realise that not all workers without one value a job guarantee and this needs to be carefully factored in to better understand job guarantee demand from workers in crisis and non-crisis times. In fact, individuals who want a job guarantee for economic reasons are willing to pay a sizable fraction of their daily wage that is higher than the sample average at 31 percent to have a guaranteed number of workdays. Compared to this job guarantee valuation for conventional reasons, there is an incremental increase in willingness to pay due to coronavirus and lockdown. This emerges from study of experimental variations in willingness to pay in the reasons why workers state they would like a job guarantee. The crisis from C19 has therefore acted to reinforce and strengthen the protective value of a job guarantee, both by expanding the set of workers who would like a job guarantee and by an incremental valuation increase.

These job guarantee findings have 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 is high on the agenda. Job guarantees are a potentially important policy lever, both because workers significantly value them for the work, income and livelihood that they provide in "usual" times and because these issues have become even more pressing now.

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Table 1: Job Guarantee, Pre-Lockdown

	All	Daily	Informal	Employee
All	0.163	0.172	0.111	0.242
Aged≤25	0.178	0.182	0.133	0.237
Aged>25	0.153	0.166	0.099	0.247
Female	0.200	0.202	0.177	0.230
Male	0.158	0.169	0.104	0.244
Education≤10th standard	0.154	0.171	0.105	0.262
Education>10th standard	0.187	0.176	0.136	0.225
Lockdown zone	0.178	0.185	0.131	0.266
No lockdown zone	0.130	0.177	0.075	0.189
Able to work at home	0.224	0.180	0.160	0.297
Unable to work at home	0.158	0.171	0.108	0.235
Number of workers	3029	850	1361	818

Table 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	0.233	0.169	0.246	-0.077 (0.020)
Zero hours	0.094	0.042	0.104	-0.062 (0.012)
Not working	0.327	0.211	0.350	-0.139 (0.022)
Sample Size	3029	515	2514	3029
B. Earnings, All				
Monthly earnings, pre-lockdown	8479	8059	8561	-502 (261)
Monthly earnings, lockdown	1285	2139	1119	1020 (265)
Percent earnings loss	85	74	87	
Sample size	3029	515	2514	3029
C. Earnings, Working				
Monthly earnings, pre-lockdown	8525	7964	8658	-694 (305)
Monthly earnings, lockdown	1680	2569	1471	1098 (332)
Percent earnings loss	80	68	83	
Sample size	2032	396	1636	2032
D. Earnings, Paid				
Monthly earnings, pre-lockdown	9134	9934	8877	1057 (723)
Monthly earnings, lockdown	7063	8470	6612	1858 (840)
Percent earnings loss	23	15	26	
Sample size	487	114	373	487

Notes: Standard errors in parentheses.

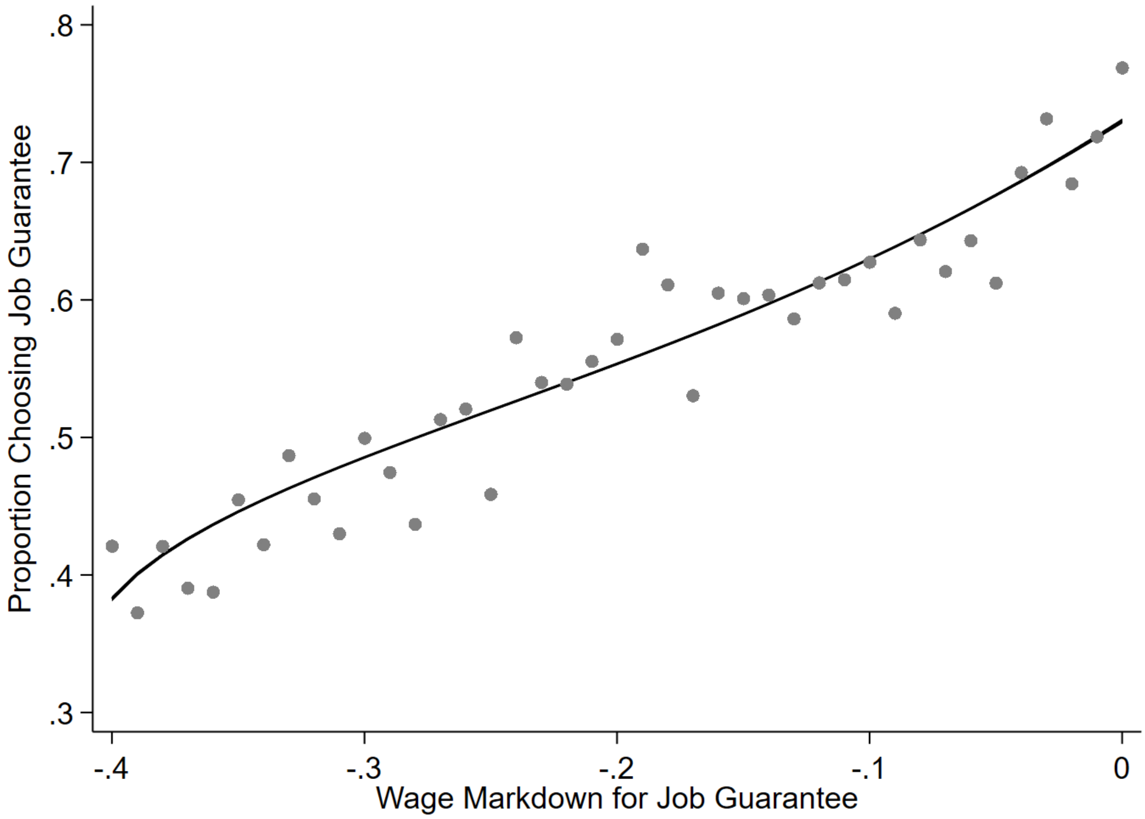
Table 3: Employment and Earnings Losses From C19

	Pr[Employment Loss]					
	Job loss		Zero hours		Not working	
	(1)	(2)	(3)	(4)	(5)	(6)
Job guarantee	-0.094 (0.020)	-0.097 (0.020)	-0.075 (0.012)	-0.072 (0.012)	-0.168 (0.022)	-0.169 (0.022)
Age	-0.002 (0.001)	-0.002 (0.001)	-0.003 (0.001)	-0.003 (0.001)	-0.005 (0.001)	-0.005 (0.001)
Female	0.012 (0.018)	0.013 (0.017)	-0.001 (0.012)	0.002 (0.012)	0.011 (0.019)	0.015 (0.019)
Education$\leq 10^{th}$ standard	-0.051 (0.020)	-0.050 (0.021)	0.002 (0.014)	-0.003 (0.014)	-0.049 (0.022)	-0.054 (0.022)
Daily	-0.084 (0.024)	-0.092 (0.024)	-0.043 (0.018)	-0.045 (0.018)	-0.127 (0.026)	-0.137 (0.026)
Informal	-0.070 (0.022)	-0.072 (0.022)	-0.057 (0.017)	-0.059 (0.017)	-0.127 (0.024)	-0.132 (0.024)
Lockdown zone		0.085 (0.017)		-0.027 (0.013)		0.058 (0.019)
Can work from home		-0.120 (0.026)		-0.050 (0.017)		-0.170 (0.030)
City and state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3029	3029	3029	3029	3029	3029

	Earnings Loss (Rs)					
	All		Working		Paid	
	(7)	(8)	(9)	(10)	(11)	(12)
Job guarantee	-1111 (237)	-1074 (233)	-1287 (287)	-1285 (284)	-390 (540)	-462 (518)
Age	4 (11)	7 (11)	9 (15)	13 (15)	68 (38)	73 (39)
Female	-134 (262)	-39 (252)	-32 (326)	23 (320)	-520 (361)	-581 (368)
Education$\leq 10^{th}$ standard	208 (184)	69 (183)	349 (266)	161 (266)	633 (576)	480 (616)
Daily	1212 (264)	1036 (259)	1827 (416)	1492 (403)	3115 (865)	3091 (827)
Informal	496 (233)	392 (224)	1040 (358)	801 (341)	1706 (618)	1608 (565)
Pre-lockdown earnings	0.738 (0.096)	0.739 (0.093)	0.632 (0.132)	0.635 (0.128)	0.163 (0.085)	0.163 (0.085)
Lockdown zone		571 (175)		588 (231)		-103 (446)
Can work from home		-3301 (539)		-3502 (587)		-791 (733)
City and state fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	3029	3029	2032	2032	487	487

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

Figure 1: Willingness to Pay for a Job Guarantee



Notes: Based on the sample of 2514 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 M_i as described in detail in the Appendix. For the logistic model slope in the Figure the median WTP corresponds to a wage markdown of -0.257 (standard error = 0.012), or 25.7 percent of the wage. This comes from the ratio of the estimated constant term (β_G = 0.872 with associated standard error 0.065) to the coefficient on the wage markdown (β_W = 0.034 with associated standard error 0.002). The sample is pooled across three experiments and standard errors are clustered by workers.

Table 4: Randomisation Tests for Choice Experiment

	p-value of F-statistic testing joint significance of wage gap dummy variables
Age≤25	0.92
Female	0.16
Education≤10th standard	0.23
Daily	0.99
Informal	0.64
Big city	0.79
Bihar	0.85
Jharkhand	0.99
Uttar Pradesh	0.83
Number of workers	2514

Notes: Based on the sample of 2514 workers who do not have a job guarantee pooled across three experiments.

Table 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	0.257 (0.012)	87	0.797		0.350	
Age≤25	0.286 (0.022)	92	0.800	0.005 (0.018)	0.370	0.033 (0.021)
Age>25	0.239 (0.015)	83	0.795		0.337	
Female	0.292 (0.028)	72	0.824	0.030 (0.017)	0.449	0.111 (0.022)
Male	0.253 (0.013)	88	0.794		0.338	
Education≤10th standard	0.261 (0.014)	85	0.817	0.074 (0.021)	0.372	0.085 (0.022)
Education>10th standard	0.243 (0.024)	92	0.743		0.287	
Daily	0.229 (0.013)	72	0.880	0.159 (0.024)	0.502	0.265 (0.011)
Informal	0.269 (0.024)	86	0.784	0.063 (0.024)	0.339	0.102 (0.010)
Employee	0.314 (0.046)	128	0.721		0.237	

Notes: Standard errors in parentheses. Based on the sample of 2514 workers who do not have a job guarantee. Column (1) is pooled across three experiments for 2514 workers, with standard errors clustered by workers.

Table 6: Mechanisms for Valuing a Job Guarantee

	Pr[Choose Job Guarantee]	Pr[Would Like Job Guarantee]	Pr[More Likely To Want Job Guarantee Under Corona Lockdown]
	(1)	(2)	(3)
Panel A			
Sure payment (Rs '000)	0.008 (0.016)	-0.013 (0.015)	-0.028 (0.016)
Wage markdown	-0.876 (0.083)		
Number of workers	1061	1061	1061
Panel B			
Had work for part of the year	0.053 (0.022)	0.084 (0.019)	0.037 (0.025)
Wage markdown	-0.823 (0.056)		
Number of workers	2514	2514	2514

Notes: Standard errors in parentheses, clustered by workers in Column (1). Sure payment is the minimum value in Rupees at which the individual chooses a sure payment over a 50/50 draw of Rupees 3000 or nothing, based on Falk et al. (2018). Had work for part of the year is 1 for individuals with less than 40 weeks of work in the twelve months preceding the survey.

Table 7: Reasons Given For Not Wanting a Job Guarantee

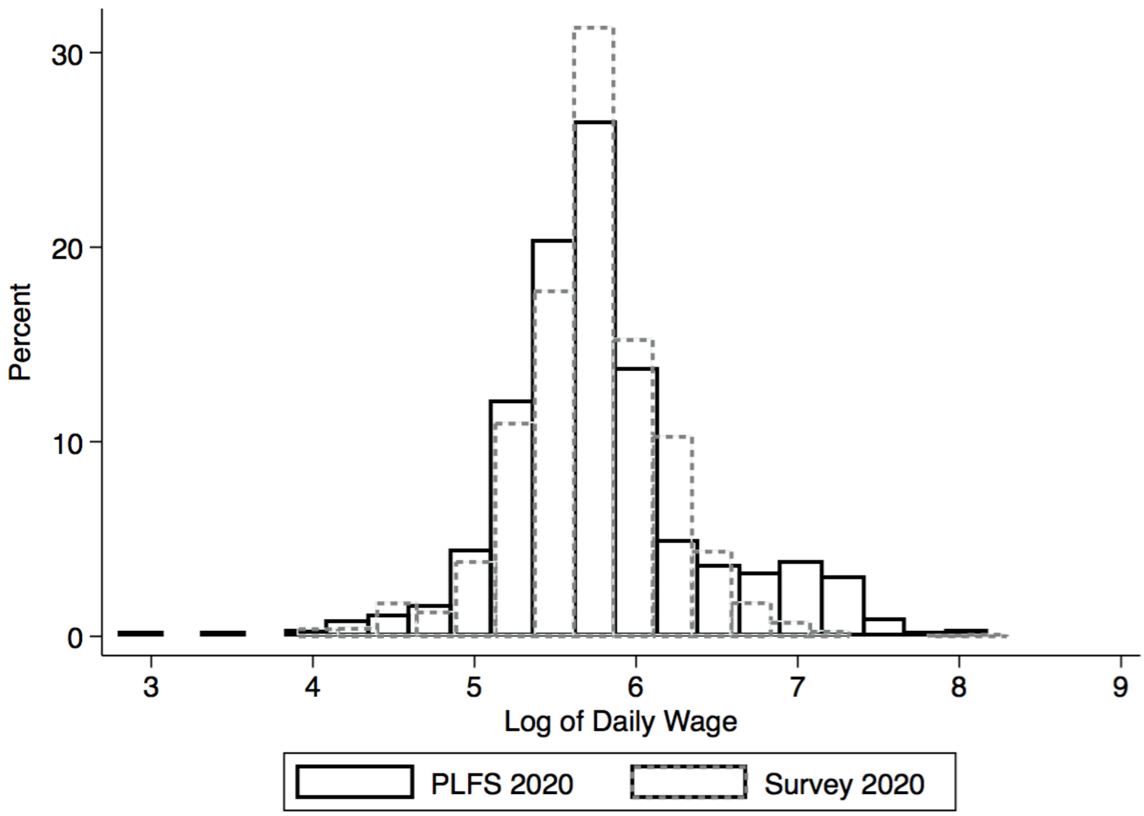
	All	Daily	Informal	Employee
Do not need it	0.617	0.599	0.611	0.638
Domestic commitments	0.214	0.092	0.278	0.180
Want to do other types of work	0.184	0.392	0.117	0.175
Student	0.048	0.032	0.019	0.104
Ill or disabled	0.011	0.004	0.014	0.012
Number of workers	497	79	248	170

Table 8: Job Guarantee Take up and Willingness to Pay by Job Guarantee and Choice Reason

	Would Like a Job Guarantee for:		
	Economic Reasons Only	C19 Reasons Only	Economic and C19 Reasons
Choose job guarantee	0.644	0.449	0.701
Choose job guarantee at no wage markdown	0.967	0.581	0.902
Have become more likely to want a job guarantee due to C19	0.318	0.683	0.388
Mean WTP	0.310	0.156	0.460
Number of workers	778	502	737

Notes: Based on the sample of 2514 workers who do not have a job guarantee in their pre-Covid employment. Economic reasons only refers to workers who say they would like a job guarantee in their pre-Covid job (or current job if the pre-Covid job is the same as the current job) for reasons of getting adequate work, livelihood security or for reasons other than C19 and related lockdowns. C19 reasons only refers to those who would like a job guarantee in the pre-Covid job for reasons related to C19 and lockdowns only. Economic and C19 reasons refer to workers who choose both types of reasons for liking a job guarantee. Choose job guarantee is the share of workers who choose the job with a guarantee in the job vignettes. Have become more likely to want a job guarantee due to C19 refers to the share of workers who say they have become more likely in the direct survey question of wanting a job guarantee more due to C19 and lockdown.

Figure 3: Wage Distributions in the Survey and PLFS



Notes: Based on the sample of 3029 workers in the survey and of 1700 workers in the PLFS. The PLFS sample refers to individuals between 18 to 40 years in the states of Bihar, Jharkhand and Uttar Pradesh who are workers according to their current weekly status in January-March 2020. National capital territory areas of Uttar Pradesh are excluded from the PLFS to match the survey design.

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, 3029 were employees or casual workers, as defined below.

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

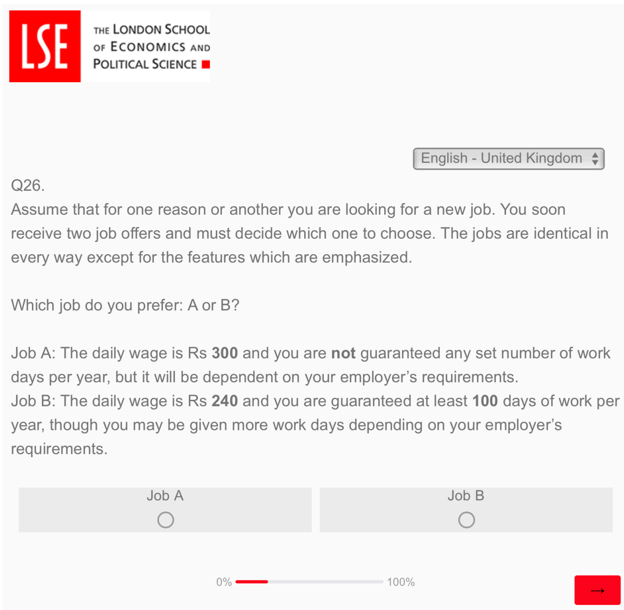
Daily Workers. Employed casually or employed by private households or employed by a single individual, and paid wages on a daily basis.

Informal Workers. Employed casually or employed by private households or employed by a single individual, and not paid on a daily basis.

Big Cities. Class I cities, which are defined by Census 2011 as urban agglomerations that had a population of 100,000 or more in the census. Each Class I city gets its own indicator and the remainder get indicators by state.

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:



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Q26.
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 emphasized.

Which job do you prefer: A or B?

Job A: The daily wage is Rs **300** and you are **not** guaranteed any set number of work days per year, but it will be dependent on your employer's requirements.
Job B: The daily wage is Rs **240** and you are guaranteed at least **100** days of work per year, though you may be given more work days depending on your employer's requirements.

Job A | Job B

0% 100%

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	-0.085 (0.021)	-0.087 (0.021)	-0.084 (0.013)	-0.081 (0.013)	-0.169 (0.023)	-0.169 (0.023)
Age	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.005 (0.001)	-0.005 (0.001)
Female	-0.011 (0.019)	-0.013 (0.019)	0.001 (0.013)	0.002 (0.013)	-0.010 (0.020)	-0.011 (0.021)
Education≤10th standard	-0.027 (0.021)	-0.026 (0.021)	-0.005 (0.015)	-0.008 (0.015)	-0.031 (0.023)	-0.034 (0.023)
Daily	-0.093 (0.030)	-0.097 (0.030)	-0.024 (0.018)	-0.024 (0.020)	-0.117 (0.032)	-0.122 (0.032)
Informal	-0.083 (0.026)	-0.082 (0.025)	-0.038 (0.018)	-0.040 (0.018)	-0.121 (0.028)	-0.123 (0.028)
Lockdown zone		0.077 (0.017)		-0.024 (0.013)		0.053 (0.019)
Can work from home		-0.130 (0.027)		-0.044 (0.017)		-0.175 (0.030)
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	3029	3029	3029	3029	3029	3029

	Earnings Loss (Rs)					
	All		Working		Paid	
	(7)	(8)	(9)	(10)	(11)	(12)
Job guarantee	-1047 (237)	-1011 (236)	-1209 (297)	-1205 (299)	-754 (586)	-811 (583)
Age	9 (11)	11 (11)	17 (15)	19 (15)	61 (36)	66 (36)
Female	201 (255)	207 (252)	444 (328)	393 (328)	173 (411)	119 (424)
Education≤10th standard	159 (190)	76 (189)	210 (277)	103 (273)	295 (589)	193 (591)
Daily	668 (261)	583 (253)	1163 (407)	990 (392)	3558 (1130)	3516 (1115)
Informal	127 (243)	84 (236)	651 (376)	523 (365)	2230 (961)	2128 (933)
Pre-lockdown earnings	0.739 (0.098)	0.741 (0.095)	0.630 (0.135)	0.633 (0.132)	0.167 (0.084)	0.167 (0.084)
Lockdown zone		585 (183)		585 (238)		-100 (475)
Can work from home		-3180 (536)		-3307 (576)		-707 (704)
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	3029	3029	2032	2032	487	487

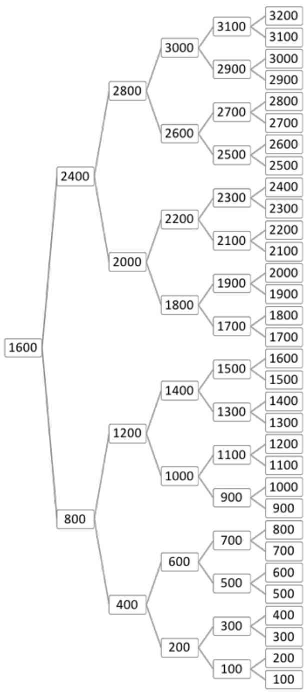
Notes: Standard errors in parentheses. The city fixed effects are for the 9 biggest cities in terms of population and the state fixed effects are for the remainder small towns or cities in Bihar, Jharkhand and Uttar Pradesh. The industry and firm size fixed effects comprise 20 industries and 6 firm size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

Table A3: Regressions For Job Guarantee Outcomes in Table 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)	-0.002 (0.001)	-0.003 (0.002)
Female	0.013 (0.021)	0.049 (0.018)	0.154 (0.022)
Education≤10th standard	0.050 (0.023)	0.039 (0.022)	0.031 (0.023)
Daily	-0.001 (0.028)	0.156 (0.026)	0.219 (0.029)
Informal	0.015 (0.026)	0.051 (0.025)	0.058 (0.025)
Wage markdown	-0.812 (0.055)		
City and state fixed effects	Yes	Yes	Yes
Sample size	2514	2514	2514

Notes: Standard errors in parentheses, clustered by workers in Column (1). The city fixed effects are for the 9 biggest cities in terms of population and the state fixed effects are for the remainder small towns or cities in Bihar, Jharkhand and Uttar Pradesh.

Figure A1: Extensive Form Game for Risk Aversion Measure



Notes: Reproduced from Falk et al. (2018), Online Appendix p.14. The up branches and down branches are increments and reductions respectively.

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 $j \in \{A,B\}$. 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 $\{0, 1, 2, \dots, 39, 40\}$. Table 5 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 Table 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.

To provide an interpretation in terms of the number of expected workdays from a job guarantee, let p_A and p_B denote the probability of getting work on a certain day in Jobs A and B, and let D_{iA} and D_{iB} denote the number of days of work demanded under Jobs A and B. Normalising $p_A = 1$, the log odds of choosing Job B which has a greater probability of providing a higher number of days than Job A ($p_B > 1$ and $D_{iB} > D_{iA}$) is $\ln(q_{iB}/q_{iA}) \approx \beta_W p_B (D_{iB}/D_{iA} - 1) - \beta_W (M_i/100)$. The willingness to pay therefore summarises the higher expectation of getting work under a job guarantee. (through higher probability of getting work on the intensive margin or through more workdays on the extensive margin): $WTP \equiv M/100 \approx p_B\,(D_B/D_A - 1)$.