Working paper

International Growth Centre

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When citing this paper, please use the title and the following reference number:
F-89462-IND-1

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Which jobs are lost during a lockdown? Evidence from vacancy postings in India*

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Abstract

We rely on real-time data from one of India's largest job portals (Shine.com) to study how COVID-19 (and the associated lockdown measures) impacted the Indian labor market. Detailed firm-level vacancy postings reveal a dramatic contraction in hiring: the number of firms posting jobs, and the number of new vacancies they list decline by 60% and 34%, respectively. Firms react to the lockdown by advertising more jobs that can be completed from home and fewer positions in occupations that can be easily automated. Furthermore, certain job-seekers are more affected than others, as employers post fewer entry-level jobs, and require higher levels of experience and education. Finally, we find that female-dominated industries and occupations are most severely impacted, suggesting the pandemic has a higher burden on women.

JEL classification: E24, J16, J23, J63, M51, O38.
Keywords: Jobs, Vacancies, Gender, Youth, COVID-19

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1 Introduction

By the end of June 2020, the COVID-19 pandemic had surpassed 10 million confirmed cases worldwide, with over 500,000 deaths. To slow the spread of the virus, countries sealed their borders, restricted domestic travel, implemented stay-at-home measures and large-scale lockdowns. The rapid spread of the virus, and the steps governments have taken to limit transmission, have dramatically affected global economic activity. According to the World Bank's Global Economic Prospects Report, baseline forecasts predict a 5.2 percent contraction in global GDP in 2020 – the deepest global recession since the Great Depression (World Bank, 2020a). This economic contraction has triggered rapid increases in job-losses. The International Labour Organization expects that over 10.5 per cent of working hours will be lost in the second quarter of 2020 alone, an equivalent of 305 million full-time workers (International Labor, 2020a).[1] In parallel, major companies and institutions have implemented hiring freezes to account for a marked decline in business revenues (Coaches, 2020). These trends suggest that the strength of any country's recovery will depend crucially on their ability to protect jobs, and stimulate business growth (UN, 2020a).

India reported its first COVID-19 case on January 30^{th} 2020. The number of cases began to rise in March, which prompted Prime Minister Modi to announce a series of (well-enforced) national lockdowns between March 22 and May 31. In this paper we partner with one of India's largest online job portals (Shine.com) to investigate how these lockdowns impacted the country's labor market. In particular, we rely on daily vacancy postings to examine how the number and composition of primarily formal-sector, urban jobs varied from January to May 2020. We estimate a series of regressions that iteratively add industry-location, firm, and firm-occupation fixed effects to further quantify the lockdown's impact, and to determine whether the trends we see come from shifts in the types of firms that post jobs, or the types of jobs that firms choose to post. While the universal nature of the pandemic

[1] They rely on index on the Google trends on the search terms related to unemployment, and Purchasing Managers' Indexes (from monthly surveys of private sector companies).

makes it difficult to determine the causal impact precisely, availability of real-time data can help mitigate these concerns. Moreover, our approach using real time data is important because it can inform the design of new programs and policies aimed at supporting certain groups of the population that are disproportionately affected by the population.

We document three important results that suggest a dramatic contraction in the labor market, especially among jobs that target young, less-educated and female job-seekers. First, the number of vacancies posted on Shine declines by 34 percent on average in the first four weeks following the lockdown. The number of "active firms", those who post at least one vacancy, also falls by approximately 60 percent. By the end of May, the decline in vacancies and active firms reaches 60 and 80 percent respectively (Figure 1). The lockdown affects all regions in India and industries on Shine.

Second, we find shifts in the *types of jobs* that are listed on the platform, namely the share of jobs that are automatable, and can be completed from home (WFH). In particular, jobs in the top 10th and 50th percentile of being 'automatable' experience sharp declines in the weeks immediately following the lockdown. Conversely, the proportion of WFH jobs rises significantly. These effects do not persist over time, however, and are driven primarily by the selection of firms that choose to post vacancies. These results suggest that lockdowns may trigger short term responses by certain firms, who begin to adapt to remote based work and temporarily suspend hiring for jobs that can be more easily automated. While we do not see a drastic reshaping of job profiles in the short run – it is conceivable that such a transition could be more sporadic, and slower to materialize (Chernoff and Warman, 2020).

Third, we investigate which *types of job-seekers* are most affected by the lockdown. First, we find that job-seekers with less education are adversely affected. By the end of May, the fraction of jobs requiring a graduate degree increases by 9.2 percent. This effect is driven both by the types of firms posting jobs, as well as the requirements demanded within firms and occupations. Second, we find evidence that younger job seekers may be disproportionately affected. The minimum experience required for a job rises by 20 percent, and the fraction of entry-level jobs falls by 40 percent. These changes are accompanied by a large increase in the average salaries jobs advertise, even within specific industries (though not within firms).

Finally, we observe a sharp decline in the fraction of job postings in female dominated occupations. Within the first few weeks of the lockdown, the number of job postings in the top 50th and 10th percentile of female dominated occupations falls by 44 and 77 percent, respectively. This effect persists for the top 10 percentile, falling to 80 percent of pre-lockdown levels by the end of May (Figure 3). The fact that female-dominated occupations are most severely affected by the pandemic in India is consistent with evidence from the United States (Pew Research, 2020), and suggests that women may be more heavily impacted by this recession than other recent economic downturns (Hoynes, Miller, and Schaller, 2012).

Our results highlight the vulnerability of young, less educated, and female job-seekers during the lockdown. Youth unemployment is already a growing concern in developing economies where 2/3 of youth are without work or engaged in irregular/informal employment (UN, 2020b). In India, nearly 1 million people join the labor market every month and struggle to find work. By exacerbating these trends, the lockdowns have reinforced – and potentially accelerated – the need to enact policies that protect existing employment opportunities and create new ones for youth. Similarly, prior to the pandemic policy makers were concerned that female labor force participation rates were already in decline in many countries including India (Nikore, 2019). Fewer labor market opportunities in the post-COVID era may aggravate this trend, and highlights the importance of implementing policies that support women's participation in the labor force.

Our results provide a clear picture of the types of jobs and job-seekers that are most affected by the lockdown, which can inform governments' programmatic response. It is also important to understand why firms reacted this way – a more challenging endeavor given the nature of these real-time indicators. Nevertheless, we explore some plausible explanations. First, we anticipate the increase in WFH and automatable jobs to be a direct response to the lockdown measures, which made it difficult to attend the office and relatively less costly to forgo hiring for easily automatable jobs. Second, the fact that firms in our sample increase skill requirements within occupations is consistent with other studies that examine firm responses to external shocks, such as the global financial crisis (Hershbein and Kahn, 2018) and increases in the statutory minimum wages (Clemens, Kahn, and Meer, 2020). These studies suggest a potential mechanism whereby firms start to invest in production technologies that require greater levels of skill. Finally, we investigate why firms post fewer jobs in female-dominated occupations. Most of this decline (68 percent) is explained by a relatively large contraction in the industries and locations where women work. Occupation specific characteristics do not seem to explain the remaining differential impact: female dominated occupations are correlated with being less automatable, and higher skill requirements/experience – all of which are trending upward. This suggests that other unobservable job characteristics may be driving these results.

Our work contributes to various strands of the literature. The fact that young job-seekers in India may have been disproportionately affected by this labor market contraction is consistent with evidence from previous recessions in the United States. Kahn (2010); Rothstein (2020) find that college students who graduate in a worse economy experience large decreases in their wages and struggle to find employment opportunities. By contrast the fact that women are disproportionately affected by this lockdown is markedly different from other economic downturns (Hoynes, Miller, and Schaller, 2012).

Our work also contributes to a growing number of studies that investigate the impacts of COVID-19 in emerging and developing economies.[2] Innovations for Poverty Action (IPA) has launched a set of surveys to measure the effect of the crisis on companies and workers. In the Indian context more specifically, there is a growing body of work that documents the impact of COVID-19 on livelihoods, but evidence on labor market outcomes remains limited (Khanna and Rathore, 2020; Chatterjee, Dey, and Jain, 2020; Lee et al., 2020; Ray and Subramanian, 2020; Deshpande, 2020). We contribute to these efforts by leveraging

[2] See IPA RECOVR website for a list of work in this space.

a new source of high frequency data that tracks how thousands of companies across India are responding to the crisis in real time. This type of analysis can help policies makers understand how labor markets are evolving, and inform the design of policies that mitigate the impacts of COVID-19 on vulnerable groups.

Lastly, our findings are consistent with literature on the labor market impacts of the pandemic in high-income countries, which has relied on real-time data from a variety of sources including credit card processors, job-portals, unemployment claims, and payroll firms (Chetty et al., 2020). Kahn, Lange, and Wiczer (2020) find that the number of Internet job postings fell by 30 percent, irrespective of the state-level policies imposed. Bartik et al. (2020) use daily data on hourly workers in US to show that job losses were concentrated among low-wage sectors, and affected disadvantaged workers more heavily.[3] In low and middle income countries, research of this nature has been limited by a lack of available data sources, even though the economic consequences of the pandemic are likely to be severe in these parts of the world (World Bank, 2020b). We fill this gap by leveraging a new source of labor market data to understand the impacts of the pandemic on one of the world's largest emerging economies.

We recognize that our results reflect the behavior of a selected sample of firms that are mostly formal and located in urban areas.[4] Nevertheless, the latest Period Labor Force Survey in India (2017) demonstrates that 58.5 percent of high-school educated workers are employed in urban areas and 38 percent of these workers have formal-sector jobs.[5] This suggests that our results are relevant for a significant share of the labor market, even if they do not shed light on how the informal sector or the rural economy is responding to the pandemic. Furthermore, governments in many emerging markets, including India, are implementing policies to bolster the formal sector, where young job-seekers are also increasingly intent on

[3]Consistent with our findings Kikuchi, Kitao, and Mikoshiba (2020) establish that female, low-skilled and younger workers in Japan are the most severely affected by the pandemic.

[4]Section B.2 finds a significant overlap between the salaries of jobs listed on Shine to those of nationally-representative workers in formal, urban jobs measured in the 2017 Periodic Labor Force Survey.

[5]A "formal" job is defined as a job where the worker has a written employment contract from the firm.

finding jobs (International Labor, 2020b). This focus on transitioning the economy to the formal sector makes it especially important to understand the implications of the pandemic on this segment of the labor market. Lastly, the magnitude of this economic shock is very large and it is unlikely that the idiosyncratic features of our sample could shift hiring trends in the way we observe in the data (Chetty et al., 2020).

The rest of our paper proceeds as follows: we begin by describing our data in section 2. We then discuss the impact of the lockdown on vacancy postings and firm activity in section 3 and across occupations and jobs in section 4. Section 5 offers a short discussion and concludes.

2 Data

Data on vacancy postings: We use a novel dataset that covers the universe of vacancy postings on Shine.com, one of India's largest national online job search portals. Our final sample consists of approximately 300,000 vacancies listed by over 12,000 unique firms on the platform from Jan 1 – May 31 2020. For each job posting we know the industry and occupation, the location, the minimum and maximum monthly salary, the date of posting and the educational and experience requirements. Industry and occupations are harmonized across jobs and coded by Shine into 65 categories, which map well into the National Industrial Classification (NIC) (see table B1) and 161 occupations, which map into the National Classification of Occupations (NCO) (see table B2).

We present the distribution of jobs before March 15th (one week prior to the lockdown). Figure B1a shows that 31.1 percent of vacancies come from the IT-Software industry, followed by manufacturing (11.1 percent), banking (9.38 percent), training (6 percent) and call-centers (5.7 percent). Figure B1b shows the distribution of job postings across occupations: 20 percent of vacancies fall under General/Other Software categories, 15 percent relate to sales, while 10 percent fall under production and quality control jobs. Other service-sector jobs such as finance/taxes, operations management, and customer service represent 5 percent of the sample each. Lastly, the vacancies are concentrated primarily in India's urban centers, with the seven major metropolitan cities (Delhi, Mumbai, Kolkata, Chennai, Bengaluru, Pune and Hyderabad) accounting for two-thirds of all postings (see Figure B1c). While detailed locations are available for the rest of the jobs (mostly Tier-II and Tier-III cities in India), we match them to their respective states. We reserve a more extensive discussion of the data for Appendix B.

We focus on the representativeness of our sample in order to interpret our findings in the context of the broader urban Indian labor market. Without detailed vacancy postings in India, this comparison is challenging. However, given the types of firms and the location of their vacancies, it is clear these jobs are concentrated in the formal sector and in urban areas. We use the latest Periodic Labor Force Survey (PLFS - 2017) to understand how the salary distribution we observe on Shine compares to the salary distribution for workers from the PLFS who have at least a high-school degree and are working in formal sector jobs. We compare these distribution across all urban areas and across the seven largest metros. Figure B2 shows that the share of high-paying jobs on Shine is slighter higher than in the PLFS because of the types of firms and workers that search on these platforms. Nevertheless, we see that Shine does a good job of capturing jobs across the entire distribution, including low-paying ones.

Data on automatable, work-from-home and female-dominated occupations: We are interested in examining whether the lockdown had differential impacts across occupations. In particular, we want to focus on automatable jobs, jobs with work-from-home capabilities, and jobs that are in female-dominated occupations. We first use data from O*NET, which assigns each occupation a score of 0-100 based on the degree of automation it contains. Jobs as travel agents, telephone operators, accountants have a high automation score, while those in music/acting, home installation, counseling and housekeeping services have low scores. We map these occupations to those on Shine, averaging the score where necessary to aggregate across detailed occupations on O*NET. Next, we use the work-from-home (WFH) classification by Dingel and Neiman (2020), who assign an indicator equal to 1 if most jobs in an occupation can be done from home, and 0 otherwise. Jobs in education, technical services and management are therefore classified as WFH, while those in agriculture, retail and construction are not. Lastly, we use India's latest Periodic Labor Force Survey (PLFS) to calculate the fraction of adult female workers in each occupation across urban areas in India. We create a dummy variable for each occupation if it is in the top 10th percentile or top 50th percentile of this distribution. Sales, purchase agents, animal husbandry, teachers, and business service agents (receptionists/secretaries) are female-dominated, while vehicle drivers, machine operators/repairmen, directors and managers are male-dominated.

3 Impact on vacancy posting and firm activity

Figure 1 shows a two-week moving average of (i) the total number of new vacancies posted on Shine and (ii) the number of firms that posted at least one job, henceforth termed as "active firms", from Jan 1–May 31, 2020. To make the interpretation easier, we normalize these outcomes to have zero mean before the first national lockdown (March 22). While the total number of vacancies remains fairly stable prior to the lockdown, it declines by approximately 34 percent within the first month of the national shutdown (Figure 1a). This decline reaches 60 percent by the end of May. The decline in the number of active firms is more gradual but the end result is equally stark (Figure 1b). The number of active firms is 60 percent lower within the first month and almost 80 percent lower by the end of May.[6]

While all major industries experienced a robust and rapid decline in vacancy postings (50-60 percent), some industries are more affected than others (Figure A2). Jobs in Information Technology (IT) and Education/Training experience a small boost post lockdown but then

[6] In appendix figure A1, we then examine the heterogeneity in firm activity across different types of firms, categorized by the number of jobs they posted before the lockdown. We find that while there is a robust decline across all categories of firms, the declines are largest (>80 percent) for the most active firms.

decline rapidly. Jobs in Banking/Finance on the other hand seem to recover to pre-lockdown levels within two months. This is consistent with the broad findings from other online job search platforms in India.[7] Turning to the geographic distribution of jobs, we classify states into five regions: North, South, East, West and Central. As shown in figure A3, we find a rapid and persistent decline of 40-70 percent across all regions.

4 Which jobs are lost?

Our results suggest India experienced a rapid and persistent decline in vacancy postings across all industries and regions. This is not altogether surprising in light of the adverse economic impacts of COVID-19 that have been documented across the world and within India. We turn next to an investigation of *which* jobs/occupations suffered the most, of which there is relatively little evidence especially in low-income countries.

4.1 Empirical strategy

First, we take advantage of the high-frequency nature of our data to examine the speed with which different variables adjust after the lockdown announcement, and the persistence of this adjustment over time. We use a two-week moving average to smooth over idiosyncratic noise. Second, we estimate a regression specification to quantify the magnitude of the impacts and examine how they vary within industry-locations and firms as opposed to across them. To this end, we estimate the following regression:

$$y_{fjrt} = \beta \text{Post}_t + [\alpha_{jr} + \alpha_f] + \varepsilon_{fjrt} \tag{1}$$

where y_{ifjrt} is the outcome variable for a vacancy posting i, posted by firm f in industry j and location r in a week t. Post_t is a dummy variable that takes the value 1 if t is after March 22nd (the first national lockdown) and 0 otherwise. In additional specifications, we

[7] See a report here.

add industry-location and firm fixed effects. β is our coefficient of interest. Following the discussions in Abadie et al. (2017) and Cameron and Miller (2015), we cluster our standard errors at the location-level.

4.2 Impact on types of jobs

Automatable jobs: One concern in the popular discourse on the impact of lockdowns has been whether firms will transition towards automating a larger share of jobs. To examine this we use the automation score from O*NET for each occupation in our sample. We then create two dummy variables that take the value 1 if an occupation has an above-median score or is in the top 10th percentile. Figure 2a shows how the fraction of jobs in the top 50th and 10th percentiles of automatable occupations change over time. Some firms seem to react to the lockdown by temporarily reducing the share of automatable jobs they list, likely because it is less costly to replace their work with alternative systems. Within a week of the lockdown, we observe a large decline of 33.8 percent and 51.4 percent for jobs that are in top 50th and 10th percentile respectively. However, we do not see persistence in this decline. By the end of May, vacancy postings in these automatable occupations are only 8 percent lower. Column (1) of Table 1 examines the change in the log automation score before and after the lockdown for the full set of job postings. The log-automation score declines by 2.65 percent after the lockdown (panel A). After adding industry-location fixed effects (panel B) the estimate falls to 1.65 percent – implying that 38% of the decline in automatable jobs is explained by the set of industries and locations that are posting vacancies post lockdown. Finally, panel C shows that when controlling for firm fixed effects, the fraction of automatable jobs falls by 0.89 percent post-lockdown. In other words, one third of the observed decline in automatable jobs comes from the particular occupations specific firms choose to post.

Work-from-home (WFH) jobs: We use a dummy variable created by Dingel and Neiman (2020) to capture whether job occupations can be classified as work-from-home (WFH) or not. Figure 2b shows how the fraction of WFH vacancies changes over time. We see a large increase (10 percent) in the share of WFH vacancies within a week of the lockdown, as firms adjust to the reality of not being able to open their offices. However, by the end of May as the lockdowns start to lift this share of WFH jobs is only 2-3 percent higher than before the lockdown. Column 2 in panel A of Table 1 highlights a 6.58 pp (7.5 percent) increase in WFH jobs after the lockdown. The increase is only 2.54 pp (2.9 percent) and 0.48 pp (0.54 percent) after controlling for industry-location and firm fixed effects. This evidence suggests that changes in WFH jobs are driven primarily by the types of industries and locations (and therefore firms) posting online (61%) rather than changes within firms over time (7%).

4.3 Impact on female dominated jobs

To understand the impact of the lockdown on different types of job-seekers, we start by searching for differential declines in job postings across male and female-dominated occupations. This is of particular interest in light of Deshpande (2020), who argues that the impact of the lockdown in India was not gender neutral. Within a few of weeks of the lockdown, we see that the top 50th and 10th percentile of female dominated occupations experience a 44 and 77 percent drop, respectively (Figure 3). Moreover, while vacancies in above-median occupations fully recover by the end of May, the decline in vacancies for extremely female-dominated occupations is large and persistent. Columns (3) and (4) in panel A of Table 1 show that vacancies decline by 9.65 pp (31.2 percent) and 4.9 pp (65 percent) for above-median and top 10th percentile of female-dominated occupations, respectively. These estimates fall to 3.2 pp (10.3 percent) and 1.54 pp (20.4 percent) after adding industry-location fixed effects, and 0.6pp (2 percent) and 0.3pp (5 percent) after adding firm fixed effects. These estimates highlight that the decline in vacancies for female dominated occupations is primarily explained by a contraction in the industries and locations where women work (67%). Firms do not appear to dramatically change the share of female-dominated occupations they post online.

We investigate whether the remaining decline in female-dominated jobs can be explained by job-characteristics. Table A1 presents how correlated gender is to other job-characteristics. We find that jobs in female dominated occupations are more likely to require graduate degrees (correlation coefficient of 0.1) and additional experience (correlation coefficient of 0.06), and are also more likely to be completed from home (correlation coefficient of 0.05). These characteristics are positively correlated with female-dominated occupations and become more in-demand post lockdown, which means they are unlikely to be driving the results we see on gender. This suggests that there may be more subtle and unobservable reasons why females are relatively more affected by the lockdown, which we leave to future research.

4.4 Impact on skill, experience requirements and monthly salary

We consider different job characteristics to understand more about the types of job-seekers that may be adversely impacted by the lockdown. These include: (i) *skill requirements*, defined as the level of education required for a job; (ii) *experience requirements*, defined as the minimum experience required for a job and the fraction of entry level jobs; and *monthly salary*, measured by the minimum and average monthly salary listed for a job. The results suggest that young, less-educated job-seekers struggle more to find jobs post-lockdown.

Skills required: Figure 4a illustrates how the fraction of jobs that require a graduate degree (relative to a high-school degree or below) changes over time. We see a significant, and rapid, increase in the fraction of jobs that require a graduate degree. The increase begins slightly before the lockdown was announced in March and persists until the end of May. Column 5 in Panel A of Table 1 confirms an increase of 8.07 pp (or 9.2 percent) after the lockdown was announced. Panels C and D show these estimates remain large – 5.02 pp (5.7 percent) and 4.6 pp (5.2 percent) – after controlling for firm and firm-occupation fixed effects. This demonstrates that 37 percent of the increase in skills demanded is driven by types of industries, locations and firms that choose to post after the lockdown. More strikingly, 57 percent of the average increase in skill requirements can be explained by firms becoming more stringent *within* occupation after the lockdown. This resonates strongly with how firms in the United States responded after the global financial crisis of 2008, and to statutory minimum wage changes (Clemens, Kahn, and Meer, 2020). Hershbein and Kahn (2018) find evidence that the recession accelerated "routine-biased technological change" (RBTC), a process whereby firms included more sophisticated technology in their production lines and hired more skilled workers to manage these new systems.

Experience required: Figure 4b shows that the minimum experience required for a job increases rapidly by 20 percent, and persists until the end of May. Conversely, the fraction of entry-level jobs (requiring less than 1 year of experience) declines by 20 percent within the first few of weeks of the lockdown. This trend intensifies as the lockdown persists, reaching 40 percent by the end of May relative to pre-lockdown averages. We expect these trends to impact youth more significantly as they typically have less experience and are targeting entry-level jobs. To quantify these impacts, we define an inverse-hyperbolic sine (ISH) transformation of minimum experience and report the results in column (6) of Table 1.[8] Panel A confirms a 16.7 percent increase in the minimum experience requirement after the lockdown. After controlling for industry-location and firm fixed effects we see the point estimates fall to 10.8 percent (panel B) and 1.5 percent (panel C), respectively. This indicates that most of the change in required experience comes from the selection of firms that are hiring. We observe little change (both in magnitude and statistical significance) in experience requirements *within* firms. We also report the results for the fraction of entry-level jobs in column (7) of Table 1. The fraction of entry level jobs falls by 22.7 percent overall. A similar trend emerges: this decline shrinks to 13.7 percent and 2.2 percent (statistically insignificant) after adding industry-location and firm fixed effects.

[8]ISH for a variable y is defined as $\ln(y + \sqrt{1 + y^2})$ and is useful since it can accommodate zeros, which we observe for minimum experience. The interpretation approximates that of a logarithmic transformation.

Monthly salary: Finally, we observe the minimum and maximum monthly salary that a firm is willing to pay (rather than the actual monthly salary). We report changes in the minimum salary, and the average between the minimum and maximum salary. Figure 4c plots the change in these two salary measures over time. The minimum and average salary increase by more than 10 percent after the lockdown is announced. The increase is rather sudden (within a week), and persists thereafter for two months. We turn to columns (8) and (9) in Table 1 to quantify this impact. We see from panel A that average and minimum salaries increased by 22.2 and 16.4 percent respectively after the lockdown announcement. These changes are similar (16.1 percent and 11.2 percent) after controlling for industry-location fixed effects (panel B). However, we see the changes are small in magnitude and statistically insignificant after we add firm fixed effects (panel C) or firm-occupation fixed effects (panel D).

5 Discussion and Conclusion

Current projections estimate that the pandemic will generate one of the largest economic recessions since the Great Depression (World Bank, 2020a). COVID-19 has spared very few countries, impacting the economies of high and low income countries alike. In this paper we focus on the effects of the pandemic on the Indian labor market, one of the world's largest emerging markets. India responded to the pandemic by imposing a swift lockdown that lasted from the end of March to May 2020. We use data from one of India's largest job portals (Shine.com) to examine employers' hiring response to these measures, and asses whether certain types of jobs and job-seekers were more affected than others.

We draw three conclusions from our analysis. First, there was a large and persistent decline in the number of vacancies and active firms after the lockdown began. Second, there was a marked shift in the types of jobs that were listed on the portal in the first month following the lockdown. The share of highly automatable jobs experienced a sudden decline, while the share of work from home jobs increased. Both recover by the end of May. These effects were driven by certain types of firms deciding that it would be less costly to advertise jobs that could be completed from home, and to suspend hiring for jobs they could more easily find alternative arrangements for.

Third, we find that less-educated, young and female job-seekers were the most severely impacted by the lockdown. We see a persistent rise in the minimum educational requirement for a job, stemming from changes in the types of jobs firms posted, as well the types of firms that posted at all. This is consistent with evidence from the US that suggests firms react to a recession by investing in technological upgrades, and a more skilled workforce. Similarly, the share of entry-level jobs fell significantly, and the minimum level of experience required increased. Finally, jobs concentrated in extremely female-dominated occupations (top 10th percentile), experienced a large and persistent decline after the lockdown. This result is driven by a sharp contraction in the industries and locations where women predominantly work. We do not find that any of this effect can be explained by the observable job characteristics we have in our sample (wage, education, experience, automation), which suggests that other factors are at play.

Overall, this paper provides evidence that the pandemic and associated lockdowns could fundamentally affect the economic landscape for certain job-seekers in India for the foreseeable future. As the number of entry level jobs requiring less experience and education falls, a greater share of young job-seekers may struggle to gain a foothold in the labor market. Similarly as women face greater barriers to entering and remaining in the labor market, their propensity to drop out of the labor force may continue to rise. While lockdowns (and containment measures more broadly) represent common policy responses to mitigate the spread of COVID-19, our results suggest that measures protecting young, less-educated and female job-seekers could become increasingly important.

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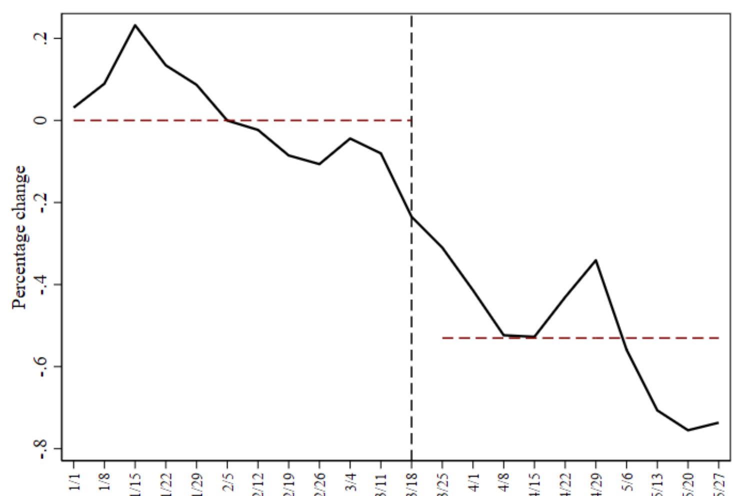
Figures

Figure 1: Impact on vacancy postings and active firms

(a) Total vacancy postings

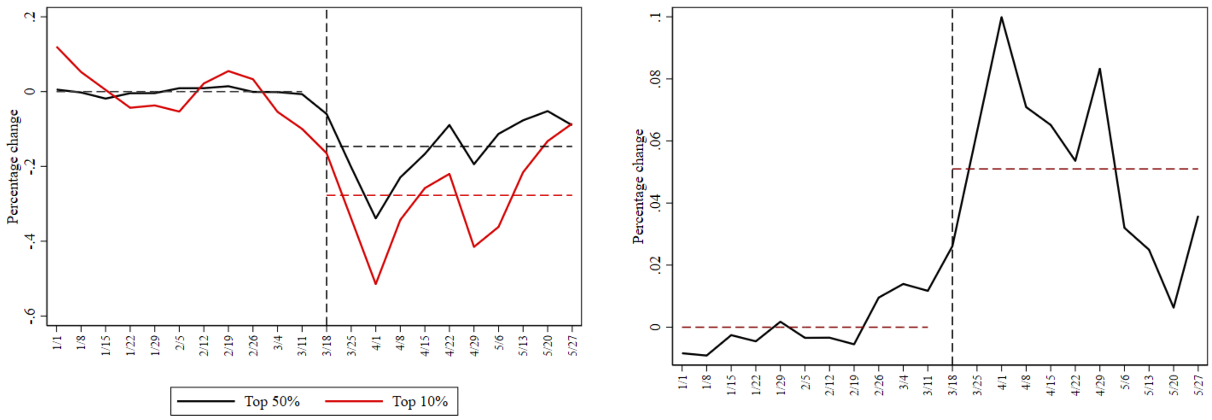
(b) Total number of active firms



Notes: Graphs (a) and (b) plot a two-week moving average of the total number of vacancy postings and "active firms" (firms posting at least one vacancy) for each week in 2020. The variable of interest is normalized to have zero mean in the pre-period (before the first national shutdown). The dotted red lines are the averages in the pre and post period. India announced a "janatā-curfew" on 03/22, followed by four lockdowns immediately after between 03/25–05/30.

Figure 2: Jobs in automatable and work-from-home occupations

(a) Automatable Occupations (b) Work from home jobs

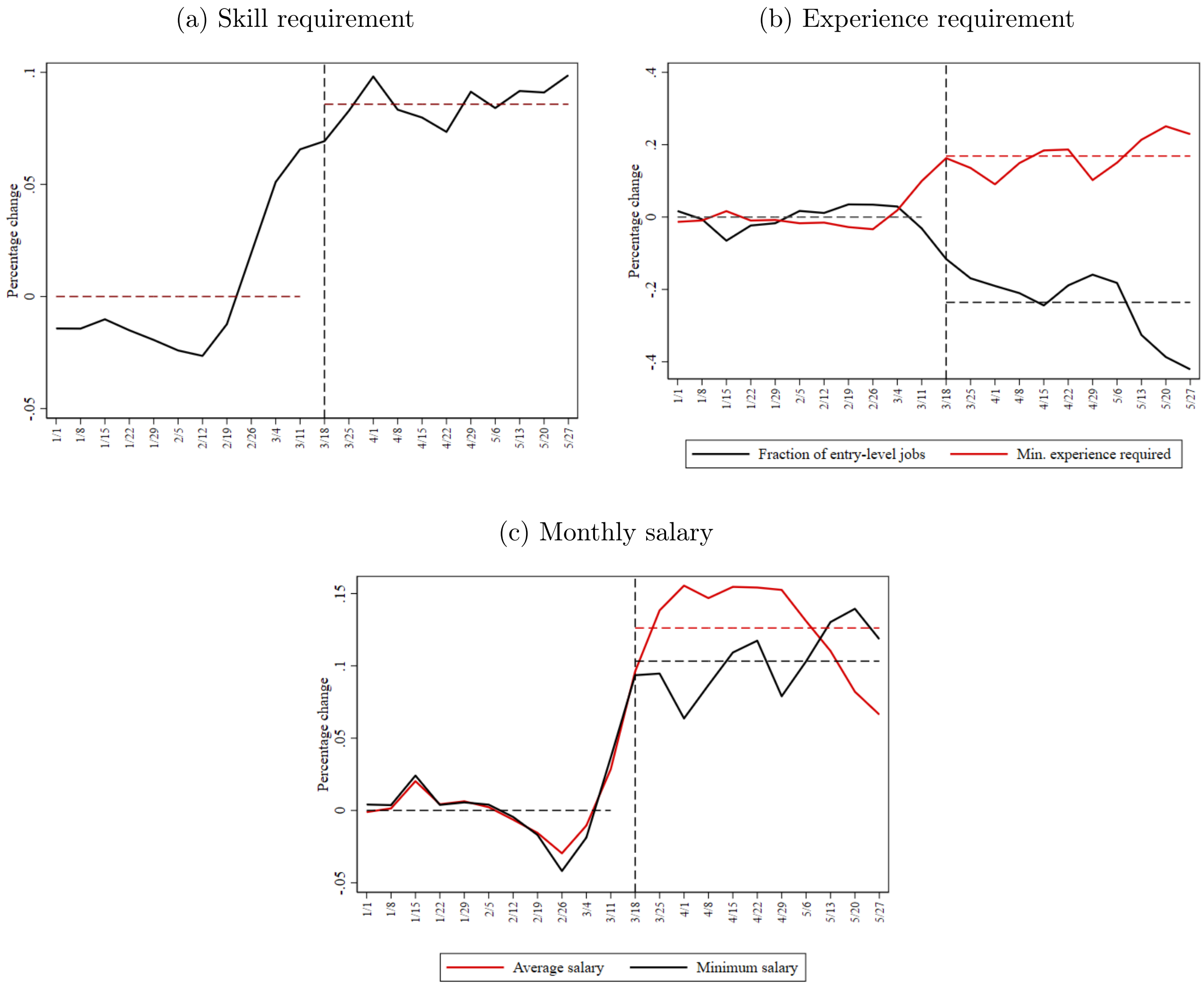


Notes: Graph (a) plots jobs in automatable occupations. We plot the fraction of jobs in the above median (top 50%) and top 10% of automatable occupations. Grpah (b) plots the fraction of jobs in work from home occupations. The variable of interest is normalized to have an average of zero in the pre-period (before the first national shutdown). The dotted red lines are the averages in the pre and post period. India announced a "janatā-curfew" on 03/22, followed by four lockdowns immediately after between 03/25–05/30.

Figure 3: Jobs in female-dominated occupations

Notes: This graph plots the fraction of jobs in female-dominated occupations. Top 10% are the occupations with 90th percentile and above fraction of female workers, as reported in the PLFS while top 50% are the occupations with above-median female workers. The variable of interest is normalized to have an average of zero in the pre-period (before the first national shutdown). The dotted lines are the averages in the pre and post period. India announced a "janatā-curfew" on 03/22, followed by four lockdowns immediately after between 03/25–05/30.

Figure 4: Impact on skill, experience requirements and monthly salary



Notes: Graph (a) plots a two-week moving average of the minimum education requirement for a job. Plot (b) plots the minimum experience required and the fraction of entry-level jobs, and the monthly salary in rupees if plot (c). The variable of interest is normalized to have an average of zero in the pre-period (before the first national shutdown). The dotted red lines are the averages in the pre and post period. India announced a "janatā-curfew" on 03/22, followed by four lockdowns immediately after between 03/25–05/30.

Table 1: Regression results

	Log Auto. Score	Frac. WFH jobs	Fem. Dom. Occ. Jobs Top 50%	Top 10%	Frac. Grad. Degree	ISH Min. Experience	Frac. Entry level jobs	Log Salary	Log Min. Salary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: With no controls									
Post	-0.0265**	0.0658***	-0.0965***	-0.0489*	0.0807***	0.167***	-0.0823***	0.222***	0.164***
	(0.0101)	(0.0117)	(0.0297)	(0.0262)	(0.00708)	(0.0436)	(0.0203)	(0.0200)	(0.0299)
Firms	12019	12019	12019	12019	12019	12019	12019	12019	12019
R^2	0.003	0.012	0.011	0.010	0.019	0.008	0.007	0.031	0.011
Panel B: With industry × location fixed effects									
Post	-0.0165***	0.0254***	-0.0320***	-0.0154*	0.0665***	0.108***	-0.0495***	0.161***	0.112***
	(0.00468)	(0.00397)	(0.0114)	(0.00783)	(0.00486)	(0.0263)	(0.0119)	(0.0148)	(0.0189)
Firms	11904	11904	8279	8279	10851	11911	11911	11013	11055
R^2	0.247	0.323	0.250	0.463	0.198	0.223	0.206	0.204	0.174
Panel C: With firm fixed effects									
Post	-0.00893***	0.00480*	-0.00620	0.00393	0.0502***	0.0147	-0.00808	0.0150	-0.00802
	(0.00268)	(0.00276)	(0.00704)	(0.00248)	(0.00443)	(0.0276)	(0.0102)	(0.0150)	(0.0231)
Firms	8936	8936	5601	5601	7950	8947	8947	8187	8236
R^2	0.390	0.515	0.480	0.705	0.402	0.497	0.444	0.549	0.448
Panel D: With firm × occupation fixed effects									
Post					0.0460***	-0.0132	0.00551	-0.00636	-0.0292
					(0.00453)	(0.0300)	(0.0106)	(0.0170)	(0.0252)
Firms					6808	7724	7724	7062	7094
R^2					0.472	0.584	0.532	0.636	0.535
N	217587	217587	82096	82096	177597	218336	218336	207441	211495
Pre-mean	3.417	0.873	0.309	0.0753	0.874	1.422	0.362	3.882	3.364
bottomrule									

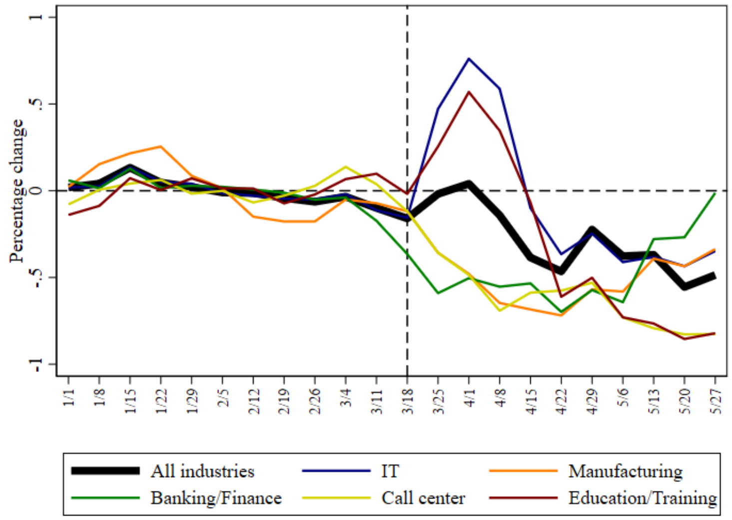
Notes: Panel A reports the regression results without any controls. Panel B adds industry-location fixed effects, panel C adds firm fixed effects and Panel D adds firm-occupation fixed effects. WFH jobs in column (2) are those jobs in occupations that are classified as work-from-home. Columns (3) and (4) report the results for the top 50% and top 5% of occupations as categorized by the fraction of female workers in them. ISH Min. Experience in column (6) is the inverse-hyperbolic transformation of minimum experience. Entry-level jobs in column (7) are defined as those jobs that require less than one year of experience. Salary in columns (8)-(9) is the monthly salary reported in rupees. Standard errors are clustered by location and reported in parentheses. * is p<0.1, ** is p<0.05 and *** is p<0.001.

A Appendix figures and tables

Figure A1: Activity across firm categories

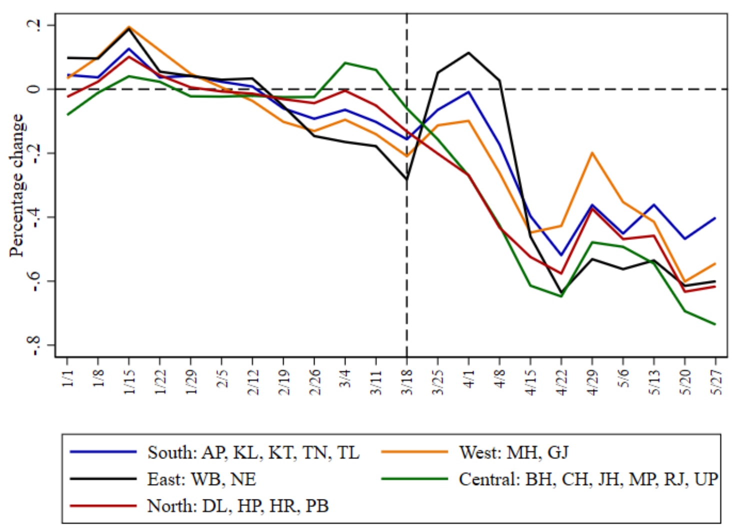
Notes: This graph plots a two-week moving average of the number of "active firms" i.e. firms that posted at least one job. We categorize firms into three categories based on their activity in the pre-lockdown period. Bottom 75% are firms that posted less than 40 jobs (75th percentile) pre-lockdown. Similarly, Top 25% and 5% are firms that posted between 41-250 jobs (75-95 percentile) and more than 250 jobs (>95 percentile) pre-lockdown. Lastly, the variable of interest is normalized to have an average of zero in the pre-lockdown period. India announced a "janatā-curfew" on 03/22, followed by four lockdowns immediately after between 03/25–05/30.

Figure A2: Activity across industries



Notes: This graph plots a two-week moving average of the total vacancy postings across industries the top five industries in our data. We normalize the variable to have zero mean in the pre-lockdown period. India announced a "janatā-curfew" on 03/22, followed by four lockdowns immediately after between 03/25–05/30.

Figure A3: Activity across states



Notes: This graph plots a two-week moving average of the total vacancy postings across regions in India. We categorize states into North, South, East, West and Central regions and normalize the variable to have zero mean in the pre-lockdown period. India announced a "janatā-curfew" on 03/22, followed by four lockdowns immediately after between 03/25–05/30.

Table A1: Correlation results

	Grad. Degree	ISH Min. Experience	Entry-level job	Log Avg. Salary	Ln Min. Salary	Ln Auto Score	WFH job	Fem. Dom. Occ. Top 50%	Fem. Dom. Occ. Top 10%
Grad. Degree	1								
ISH Min. Exp.	0.15***	1							
Entry-level job	-0.16***	-0.85***	1						
Log Avg. Salary	0.06***	0.73***	-0.6***	1					
Log Min. Salary	0.09***	0.74***	-0.62***	0.94***	1				
Ln Auto Score	-0.07***	-0.15***	0.17***	-0.15***	-0.13***	1			
WFH job	0.22***	0.19***	-0.19***	0.11***	0.09***	-0.03***	1		
Fem. Dom. Occ.									
Top 50%	0.1***	0.04***	-0.08***	-0.03***	0.01**	-0.14***	-0.18***	1	
Top 10%	0.1***	0.06***	-0.11***	-0.04***	-0.02***	-0.57***	0.05***	0.43***	1

Notes: Grad. degree are jobs that require a graduate degree or above, ISH Min. Experience is the inverse-hyperbolic transformation of minimum experience. Entry-level jobs are defined as those jobs that require less than one year of experience. Salary in columns is the monthly salary reported in rupees. WFH jobs are those jobs in occupations that are classified as work-from-home. * is $p<0.1$, ** is $p<0.05$ and *** is $p<0.001$.

B Data details

In this section, we provide more details on the composition of the data as well as the variables that are used in our analysis. In section B.1, we begin by describing the structure of the industries, occupations and locations in our data as well as how we classify them into various categories (automatable, work-from-home, etc.). In section B.2, we then examine the representativeness of our data using a nationally representative survey in India, the Periodic Labor Force Survey (2017).

B.1 Definitions and classifications

Industries: Shine classifies all jobs into 65 industries (see list in B1). These can be mapped into the National Industry Classification (NIC) that is commonly used across all national surveys in India. Figure B1a then shows the distribution of jobs before March 15, 2020 (one week before the first lockdown) across these industries. As we can see, around 30 percent of jobs are concentrated in IT-Software, followed by around 10 percent each in Manufacturing and Banking/Financial services. Education/training, call centers, hotels/restaurants and management consulting. account for around 5-8 percent each. The rest account for less than 5 percent. Given the lack of a representative dataset on vacancy postings, it is hard to verify whether these job postings are representative of the vacancies in these sectors. However, they are comparable to the jobs posted on other major job platforms in India.

Occupations: Occupations on Shine are classified into 161 categories (see table B2 for a complete list). For the purposes of the paper, we match these occupations manually to the National Classification of Occupations (NCO) to be able to match them to female-dominated occupations. We also manually match them to the Standard Occupational Classification (SOC), which is used by both ONET and Dingel and Neiman (2020), to be able to classify jobs in that occupation as automatable or work-from-home respectively.

Table B1: List of industries

Agriculture/Dairy, Animation, Architecture/Interior Design, Astrology, Automobile/Auto Ancillaries, Aviation/Airline, BPO/Call Center, Banking/Financial Services, Broking, Cement/Building Material, Chemical/Plastic/Rubber/Glass, Consumer Durables/Electronics, Education/Training, Engineering/Construction, Environment/Waste Management, Export-Import/Trading, FMCG/F&B, Fertilizers/Pesticides, Fresher (No Industry), Furnishings/Sanitaryware/Electricals, Gems/Jewellery, Gifts/Toys/Stationary, Government Department, Hotel/Restaurant, IT-Hardware/Networking, IT-Software, Industrial Design, Insurance, Internet/E-Commerce, KPO/Analytics, Legal, Logistics/Courier/Transportation, MFI (Micro Finance), Management Consulting/Strategy, Manufacturing, Matrimony, Media/Dotcom/Entertainment, Medical/Healthcare, Merchant Navy, Metal/Iron/Steel, Military/Police/Arms & Ammunition, Mining, NBFC (Non Banking Financial Services), NGO/Social Work, Oil & Gas/Petroleum, Paint, Paper/Wood, Personal Care/Beauty, Pharma/Biotech, Politics, Power/Energy, Printing/Packaging, Quality Certification, Real Estate, Recruitment Services, Retail, Sculpture/Craft, Security/Detective Services, Sports/Fitness, Telecom/ISP, Textile/Garments/Fashion, Travel/Tourism, Unskilled Labor/Domestic Help, Veterinary Science/Pet Care.

Figure B1b shows the distribution of jobs posted before 15 March 2020 across occupations. Given that around 30 percent of the jobs are in IT/Software, it is not surprising therefore that around 20 percent of them are in General/Other Software categories. This is followed by around 15 percent jobs in sales. In line with jobs in manufacturing jobs being the second most likely industry, production and quality control jobs are around 10 percent each. Other service-sector jobs such as finance/taxes, operations management, customer service etc. are 5 percent each.

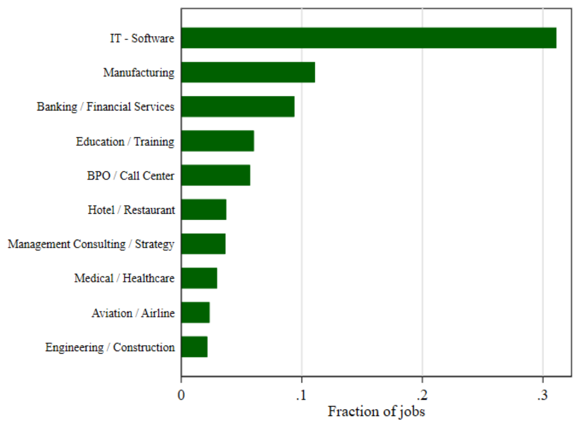
Locations: Lastly, we turn to examining the distribution of jobs across locations. Each vacancy posting reports the city/town that the vacancy is listed. We find that two-thirds of the jobs on Shine are in the seven largest metros of India, namely: Delhi, Mumbai, Kolkata, Chennai, Bengaluru, Pune and Hyderabad, with the remaining one-third in tier-II and tier-III cities across India. For the regressions, we aggregate jobs that are not in the seven large metropolitan cities to the state level. This is consistent with the popular narrative regarding the presence and operation of these online job search methods in India.

Table B2: List of occupations

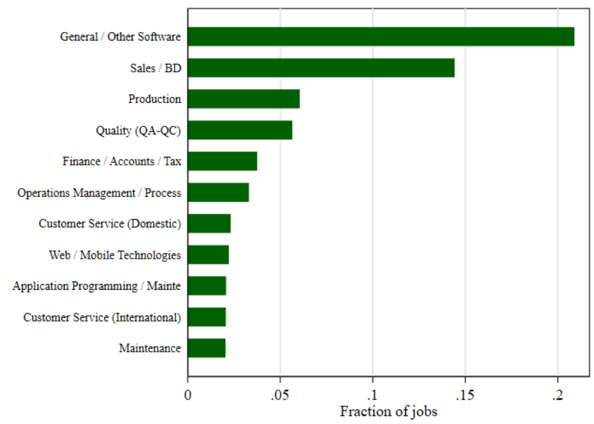
Actor/Anchor, Acturial Science, Administration/Facility/Transport, Airport/Airline Ground Operations, Allied Health Services, Animal Husbandry, Application Programming/Maintenance, Architecture, Audit, Back Office Operations, Beautician/Stylist, Bio Tech/R&D/Scientist, Cabin Crew, Career/Education Counselling, Cinematography, Civil Services, Client Server, Company Secretary, Content Development, Copywriting, Corporate Legal Department, Curriculum Design, Customer Care Executive, Customer Care Executive (Call Centre), Customer Care Executive (Rel Centre), Customer Care Executive (Repair Center), Customer Service (Domestic), Customer Service (International), DBA/Datawarehousing, Data Entry, Detective Services, Direction/Editing, Distributor Sales Rep, Doctor, Documentation/Shipping, ERP/CRM, Education Management/Director/Principal, Embedded/System Software, Embedded, VLSI, Engineering Design/Construction, Entrepreneur, Environment, Equity Research, Event Management, Executive Assistant (EA), F&B Service, Fashion/Textile Design, Fashion Modelling, Field Sales Executive, Finance/Accounts/Tax, Fire Prevention/Control, Front Office/Guest Relations, Front Office/Receptionist, General/Operations Management, General/Other Software, Geology, Graphic Design, HR, Handset Repair Engineer, Hardware/Telecom Equipment Design, Housekeeping, IT Operations/EDP/MIS, In-Store Promoter, Interior Design, Internet Marketing, Inventory/Warehousing, Investment Banking/M&A, Journalism/Writing, Kitchen, Language/Translation, Legal Support Services, Liasion, Library Management, Mainframe, Maintenance, Management Consulting/Strategy, Marine Deck Department, Marine Engineering Department, Marine Service/Steward Department, Market Research (MR), Media Planning/Buying, Medical Transcription, Merchandising/Sourcing, Middleware, Military, Mining, Music, NGO/Social Work, Network/System Administration, Networking, Nursing, Occupational Health/Safety, Oil & Gas Engineering, Operations Management/Process Analysis, Optical Fiber Splicer, Optical Fibre Technician, Painting, Pharmacist/Medical Representative, Photography, Pilot, Plantation/Farming, Politics, Pre-Sales, Pre-School/Day Care, Process Control, Product Management, Product Marketing, Production, Production, Production Design/Art, Professional/Soft Skills Training, Professor/Lecturer, Programming/Scheduling, Property Management, Public Relations (PR), Purchase, Quality (QA-QC), R&D/Product Design, Real Estate Consultant/Agent, Recruitment, Reservation/Ticketing, Risk/Underwriting, SBU Head/CEO/Director, Sales/BD, Sales Executive (Broadband), Sales Support/MIS, Sculpture/Craft, Secretary/PA/Steno, Sector/Business Research, Securities Trading, Security Services, Self Employed/Freelancer, Service/Installation/Repair, Site Engineering/Project Management, Sound Mixing/Editing, Special Education, Sports/Fitness, Statistics/Analytics, Supply Chain/Logistics, Teacher/Tutor, Teaching Assistant, Technical/Process Training, Technical Support/Helpdesk, Technical Writing, Telecom Network Design/Management, Telecom Software, Testing, Tour/Travel Guide, Tour/Travel Management, Tower Technician, Unskilled/Manual Labour, Visual Effects, Web/Mobile Technologies, Web Design.

Figure B1: Industries and locations of Shine jobs

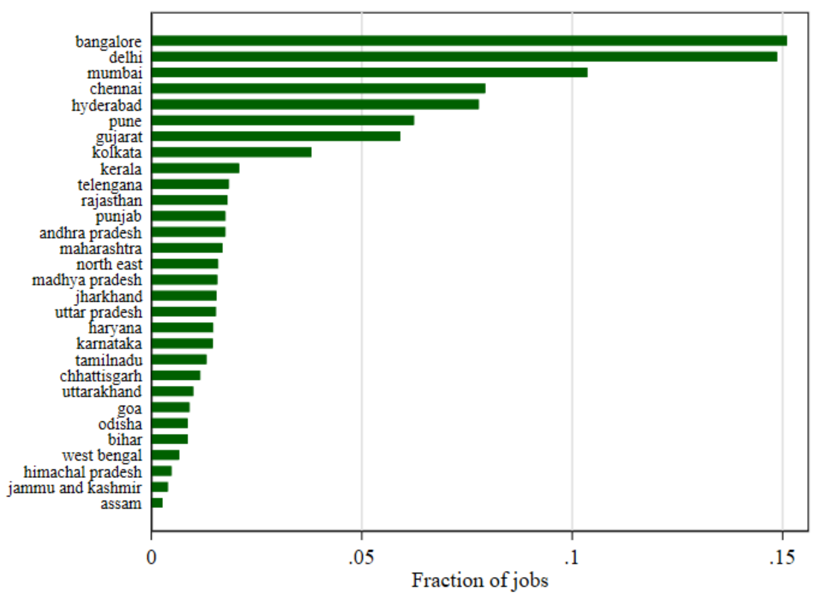
(a) Across industries



(b) Across occupations



(c) Across locations



Notes: Graphs (a) and (b) show the fraction of jobs posted before 15th March, 2020 across industry and occupations. All industries and occupations accounting for less than 2% of total jobs are omitted. Graph (c) shows the distribution of jobs across states and seven largest metropolitian cities.

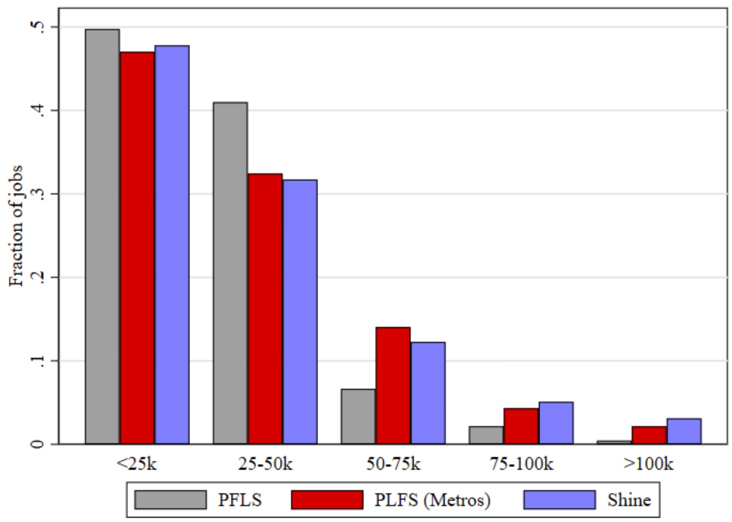
B.2 Representativeness of the data

In this section, we discuss the representativeness of our data in the context of the broader Indian labor market. Unfortunately, there is no standard dataset on vacancy postings available in India. However, to make progress, we examine how the minimum salary for the job posted on Shine compares to the salary earned by a representative set of workers in the Indian labor market, as reported in the Periodic Labor Force Survey (PLFS). To make the comparison more meaningful to the jobs posted on Shine, we restrict the PFLS to cover at least high-school educated workers in formal, urban jobs. Lastly, given that two-thirds of the jobs on Shine are in the seven largest metropolitan cities, we also compare the salary distributions specifically in these cities to those on Shine.

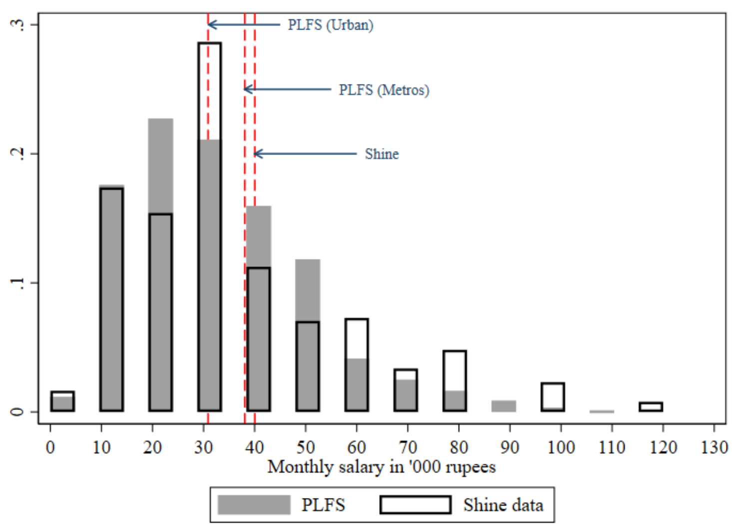
In figure B2, we plot the fraction of jobs in the PLFS and Shine, categorized in bins of Rs. 25,000 intervals. As we can see, jobs on Shine are well represented across the entire salary distribution of jobs in the PFLS (the whole sample as well as those in metros). Figure B2b then compares the distribution in Rs. 10,000 intervals. We see that Shine tends to over-represent jobs that are higher-paying, even though the average salary across the PFLS and Shine are not significantly different. Moreover, as before, Shine captures jobs across the entire salary distribution. Put together, this gives us confidence that the patterns we see on Shine do capture jobs from the entire distribution of workers and firms who potentially work in them.

Figure B2: Comparison of Shine jobs with the PLFS

(a) Across salary categories



(b) Distribution of salary



Notes: Graph (a) compares the distribution of the salary posted on Shine before March 15, 2020, and the salary reported by workers in the PLFS (2017). We restrict the jobs in the PFLS to cover high-school (and above) educated workers in formal, urban jobs. Graph (b) then plots the salary distribution between the Shine jobs and those in the formal sector in urban areas. The vertical dotted lines indicates the average salaries in each category.

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