The Benefits and Costs of Guest Worker Programs: Experimental Evidence from The India-UAE Migration Corridor

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Abstract

We estimate the returns to temporary migration programs using a randomized control trial with several thousand job seekers in India applying to guest worker jobs in the United Arab Emirates (UAE). Working with construction companies and the UAE Ministry of Labor, we randomized job offers to potential migrant workers at recruitment sites. We measured effects on labor market outcomes, well-being, social relationships, and work satisfaction, as well as on labor intermediation costs, assets and debt. We find that workers who received the randomized offer experienced 30% higher earnings, and migrating to the UAE doubled their compensation. However, they also paid substantial upfront costs to labor intermediaries, financed by additional debt, that reduces take-home pay by up to 10%. Workers offered a UAE job also experienced more diverse friendship and co-worker networks, but also report a significant fall in subjective well-being. This is consistent with the large share of workers offered jobs that do not migrate to the UAE. Extrapolating using a linear marginal treatment effects framework, we find that since there are large and positive pecuniary returns to migration for workers offered a UAE job who decline, significant non-pecuniary costs to guest worker programs are needed to rationalize the lack of take-up.

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1 Introduction

Increasing migration from poor to rich countries has potentially large impacts on global welfare and inequality. However, policies to facilitate such migration are politically controversial, as migrant workers may be willing to accept employment conditions and wages that are considerably worse than native workers, and native workers may bear the brunt of lowered wages. Ruhs (2013) documents a trade-off between the quantity of migrants a country permits and the mobility and rights accorded to those migrants. At one extreme end, non-democracies like Gulf Cooperation Council (GCC) countries implement huge guest worker programs that allow migrants temporary visas with no pathway to citizenship. The scale of these programs (relative to the size of local population) is enormous; in the UAE, more than 90% of the private workforce are migrants on guest worker visas with the vast bulk from South Asia. The guest worker programs offer very limited job mobility for the duration of the visa, which affects the balance of power between firms and workers (Naidu, Nyarko and Wang 2016). Owing to the potential scope for exploitation, such contracts have been panned as repugnant economic transactions (Clemens 2018). At the same time, many economists argue that guest worker programs are among the highest return anti-poverty programs, relying on quantitatively large earnings differentials and the fact that workers are choosing to migrate.

Despite the considerable amount of policy debate, quantitative evidence on the costs and benefits of guest worker programs remains scarce. We conduct a large-scale randomized evaluation of the effects of UAE construction job offers in India. We partnered with the UAE Ministry of Labor (MOL) and two large, private construction firms.[1] We follow UAE job recruiters around several different states in India to survey potential migrants at baseline. In addition to the more common focus on earnings, our paper provides causal estimates of the non-pecuniary benefits and costs of a construction job offer in the UAE as well as the pecuniary costs. We collected four rounds of survey data: one baseline, two tracking surveys, one follow-up survey. Our survey data include information on various work outcomes including earnings and employment, hours, and reservation wages, as well as other outcomes such as subjective well-being, work satisfaction, and social isolation. We also consider how the experience of international migration can expose people to new groups and new experiences, leading to changes in their attitudes about groups of people, inequality and democracy. In the international migration context, a particularly salient cost is the expense of labor brokers, and we ask detailed questions about the contracts between prospective migrant workers and labor market intermediaries, as well as debt taken on to finance these costs.[2]

[1] The MOL is now called the Ministry of Human Resources and Emiratisation.

[2] To our knowledge, the literature also lacks information on how the costs and benefits are born by workers,

We find that the pecuniary returns from guest worker migration are large, consistent with previous work. While they are attenuated by the costs paid to labor intermediaries, they are amplified when in-kind compensation of food and lodging, provided by UAE employers, are included. Despite these large returns, roughly 50% of the treatment group do not take the offer to go to the UAE, but instead chooses to stay and work in India. The presence of a large share of "never takers", despite large estimated pecuniary returns, suggests significant non-pecuniary disamenities from guest-worker migration.[3] Consistent with this interpretation, we find significant negative effects on subjective well-being, and some measures of job quality.

In addition to estimating the impacts of the offer on a variety of outcomes, we also make use of questions about their expectations at baseline and their reservation earnings for switching locations at the endline. Our data on expectations at baseline allows us to examine whether potential migrants have accurate information about their earnings prospects at the destination country. This is particularly important in this migration context where policymakers are concerned that workers are being deceived by unscrupulous labor intermediaries. However, there has been little large-scale evidence comparing expectations and realizations for migrants of guest worker programs.[4] Similarly, we have novel data in the context of guest worker programs on how much a migrant in the UAE would need to earn to return home to India, and how much a worker in India would need to migrate to the UAE. These questions provide a way to calculate an alternative summary measure of the disamenity value associated with being a migrant in the UAE.

Finally, we estimate marginal treatment effects of migration using the randomized offer as an instrument, and, under a linear marginal treatment effect assumption (Brinch et al. 2017), impute the effects for always-takers (who migrate despite not receiving the randomized offer) and never-takers (who do not migrate when given the randomized offer) in the counterfactuals to their observed choices. While marginal treatment effects (MTEs) have been extensively examined in a variety of settings in applied microeconomics, their implementation in the context of migration is much less common, despite their tight connection to the Roy model (Vytlacil 2002) widely used to study migration (i.e. Borjas 1986). We find considerable heterogeneity in the marginal treatment effect for well-being: never-takers have significantly lower well-being than compliers or always-takers, suggesting that there is considerable heterogeneity in the taste for guest worker migration.

firms and labor intermediaries.

[3] The evidence we present on this is also consistent with Lagakos, Mobarak and Waugh (2018) whose structural model suggests that high disutility at the destination explains the lack of subsequent remigration among seasonal migrants in Bangladesh.

[4] Shrestha (2020) uses expectations to predict the decision to migrate internationally but does not compare expectations with actual realizations.

Our context is a unique and a uniquely important one. The migrant flow between South Asia and the GCC countries is relatively understudied, despite it being the second largest circular international migration corridor in the world after the U.S.-Mexico (Azose and Raftery 2018). Over 90% of the private workforce in the UAE are migrants, and 40% of the UAE migrant population is from India. The nature of migration from India to the UAE is very different from Mexico to the U.S. as the vast majority of migrants in our context migrate legally on two-year guest worker work visas that can be renewed, with illegal migration being relatively rare.

The role of labor intermediaries for international migration in our context is also important.[5] For workers, labor intermediaries are essential for getting an international jobs. For example, 100% of workers in our sample who go to the UAE used a labor intermediary, paying on average 64,000 INR each. Paying these labor brokers represents the key financial cost to migration, and accounting for these costs is necessary for accurate estimates of the returns to migration. We are the first to combine a randomized experiment with individual-level data on the prevalence and costs of these labor brokers. We can use our estimates to calculate how much of the gains from international migration is captured by intermediaries. In this, we are related to a literature has emerged on the role of intermediaries in trade and globalization.[6] As we detail below, agent fees in our context are close to 100% of the annual guest worker premium in the UAE, and about five times higher, relative to the migration premium, than the Mexico-U.S. fees for intermediaries. Concerns about labor broker fees have stimulated numerous regulations, from governments on the sending and on the receiving side as well as the International Labour Organization, albeit with limited success. Estimating the net returns from migration requires accounting for the costs migrants pay to labor market intermediaries.

Our paper contributes to a large literature estimating the impacts of international migration. The key issue in this literature is how to address the fundamental selection in who decides to migrate. Most of the existing literature on international migration uses natural experiments and other methods to solve the selection problem and this literature has often focused on the Mexico-U.S. migration corridor (see surveys by Clemens 2011, McKenzie and Yang 2012). In terms of methodology, we are most similar to the literature that solves the selection problem with visa lotteries. Prior research exploiting visa lotteries for permanent migration has found large positive effects on earnings: 263% for Tongan immigrants to New Zealand (McKenzie et al 2010) and

[5] Intermediaries are also called labor brokers or agents.

[6] Atkin and Donaldson (2015) show that intermediaries capture a significant share of the gains from trade liberalization. In agricultural markets, Bergquist and Dinerstein (2020), Dhingra and Tenreyro (2020), and Macchievello and Mojaria (2021) have studied the role of imperfectly competitive intermediaries in agricultural markets. In labor economics there has also been a literature on labor market intermediaries such as temp agencies (Autor 2008, Drenik et al. 2020).

\$58k for Indian programmers in U.S. (Clemens 2013). The literature has also found ambiguous effects on well-being, with improved mental health (Stillman et al 2009), but worse blood pressure and hypertension (Gibson et al 2013), and lower happiness and respect (Stillman et al. 2015). However, the returns to permanent migration to countries like New Zealand and the U.S. that take in very few migrants (relative to their size) and give migrants a lot of labor market mobility as well as broader economic and political rights is likely to be very different from the returns to the large-scale guest worker programs operated by the GCC countries.

Research focusing on guest worker migration programs is quite nascent, despite long-standing claims by economists, including Weyl (2018), that such programs are the most effective way to reduce global inequality.[7] Clemens (2017) looks at the same migration corridor and finds a 300% earnings returns for Indian migrants to the UAE using a natural experiment of contracts cancelled during the financial crisis.[8] Gaikwad et al. (2022) implement a randomized experiment of job training and interview access for service jobs in the UAE, but have a much smaller sample of 248 migrants from one state in India (Mizoram) and cannot disentangle the impacts of training from job placement. A recent paper on guest worker programs in another context is Mobarak et al. (2021) which finds a 60% return to household income using a visa lottery of Bangladesh-Malaysia migration.[9] Further, none of the prior literature on the returns to guest worker programs accounts for the costs of labor market intermediaries, or measure the contractual arrangments brokers have with workers. Finally, the focus in our paper on the migrant rather than the household allows us to be the first study on guest worker programs to consider to what extent the gains in earnings are offset by worse work amenities and lowered subjective well-being of the workers.

The dimensions of subjective well-being are important. Individual migrants, separated from their primary social networks, may also bear large psychological costs. Reports of loneliness and alienation among migrant guest workers are common (Ponizovsky and Ritsner 2004). We are also able to look at other ways migration changes an individual, including their friendship and co-worker networks. While migrants experience isolation from their pre-existing social networks, migration also potentially exposes workers to much more diverse co-workers and the opportunity to form new social ties. The exposure to new groups of people may be particularly important in the context of India where intergroup conflict, often defined by religious groups, is signifi-

[7]Similarly, Rodrik (2007) writes,"A guest worker program is the most effective contribution we can make to improving the lives of the world's working poor."

[8]The returns during a large economic contraction may be quite different from other times.

[9]Because this paper relies on a past lottery event and tracks workers from administrative data five years later, they use a non-random sub-sample of visa lottery participants. Furthermore, the Bangladesh-Malaysia context is very different from the bulk of migration to the Gulf, because Bangladesh has a centralized lottery system, while migration in India is decentralized and serviced by an extensive market of labor intermediaries.

cant. Thus, we also examine whether migration changes attitudes about other religions and nationalities a worker is exposed to in the new country. This result ties into an existing empirical literature that tests Allport's (1954) theory that intergroup contact can reduce prejudice towards others.[10] Research outside of economics has considered whether interactions generated by migration affects prejudice (e.g. Gessler, Toth and Wachs 2021, Hangartner et al 2019) but the focus of this prior literature has been on how exposure to migrants affects natives' attitudes about migrants rather than how the experience of moving to a different country affects migrants' attitudes towards both natives and other groups.

Other research on guest worker programs has focused on changing features of guest worker programs on both wages and employer market power (Naidu, Nyarko, and Wang 2016), or information experiments, such as informing Nepalese workers about mortality rates (Shresta 2017). Kosack (2021) shows that such temporary migration programs encourage human capital investments, and Weyl (2018) stresses the contribution GCC guest worker migration makes to reducing global inequality, even as Piketty et al. (2020) describe the exceptional levels of inequality within these countries as the highest in the world.

The rest of the paper proceeds as follows. We present more details on the context, the experiment and data collection in the next sections, along with summary statistics on the selection of migrants by firms. We then describe our estimation strategy. Next, we present results on a variety of labor market outcomes, as well as effects on labor market intermediary payments. We also examine other impacts including well-being, work satisfaction, financial outcomes, attitudes and social networks. In our last section, we look at heterogeneity in outcomes. This includes integrating our results via a generalized Roy model of migration, describing the effects on compliers, always-takers, and never-takers.

2 Background on the Migration Supply Chain

The recruitment of migrants to GCC countries is a decentralized process throughout India. On the employer side, firms acquire authorization for visas from the UAE Ministry of Labor. Next, the firms work with a labor recruitment company who sets up interviews at recruitment sites in around India. Then, the firm applies for visas for the specific individuals who have passed the screening interviews. In our sample, the labor recruitment company was based in Singapore and subcontracted with labor intermediaries in India to set up interviews at construction training centers. Agents

[10] Lowe (2021) provides a recent review of this literature, which has used randomized variation to show that intergroup contact reduces prejudice in sports teams (Lowe 2021, Mousa 2020) and in classrooms (e.g. Rao 2019).

physically accompany applicants to the interview location. Applicants undergo a skills test involving actual construction materials in front of a recruiter from the company in UAE, and are offered a job if they pass.

On the worker side, the search process through which they find out about job opportunities, and travel to interview sites are facilitated through a large and informal industry of labor brokers. Further, there are a large number of ancillary tasks and expenses. A valid passport is necessary at the interview stage. After securing an offer, the workers need to get additional documents in order, and pass a health screening. The flight to the UAE is paid for by the firm in the UAE.[11] Local brokers are universally used by Gulf-bound migrants, and our sample is no exception, as shown in Panel A of Table 1, where 100% of UAE migrants pay brokers for migration services.

Concerns about the exploitative nature of these contracts abound, but there has been little quantitative and representative evidence on these contracts. We asked all the potential migrants in our sample about the contracts with agents and the payment structure. In Table 1, we provide descriptive statistics from the sample of migrants on the nature of the contracts signed. The overall costs for a migrant are large, averaging 64,442 INR (over USD 1000). This corresponds to about 40% of the annual income of the Indian household at baseline. The agent fee entails two components: an upfront cost paid by every prospective applicant and a second fee that is only paid contingent on a successful job match in the UAE. The upfront costs are a relatively small share of the costs (INR 1615 or 2.5% of the total fee). The vast bulk of the costs are contingent and paid only by the individuals who secure a job offer in the UAE. The contingent fees are paid prior to leaving for the UAE, so migrants incur a substantial level of debt in order to do so.

The 1983 emigration act, which required emigrants for work to acquire authorization from the Protector of Emigrants at the Ministry of Overseas Indian Affairs, was passed in wake of the rise of emigration to the GCC countries in the 1970s. The act required international labor recruiters to be licensed by the government, and for overseas firms to recruit via a licensed recruiter. However, enforcement of some aspects of the regulation around migrant recruitment has clearly been ineffective. For example, survey evidence indicates that agent fees regularly exceed the INR 10,000 maximum prescribed by the law.[12]

The multiple levels of intermediaries create ample scope for the gains from international migration to be dissipated. However, the descriptive evidence presented in the section cannot tell us the extent to which the fees offset the earnings effects of

[11]Panel A of Table 1 shows the services that the agent provided for the migrant.

[12]This includes our survey as well as Rajan et al (2009) who in a sample of 88 international emigrants from India find the average total cost of international migration among those working with recruiting agents to be about INR 51,000.

migration. For example, workers with higher expected wages or tastes for migration may pay agents more. We leverage our randomized experiment to produce the first causal estimates of the costs of migration associated with these intermediaries.

3 Experimental Design and Data Collection

We partnered with two large construction firms in the UAE and the UAE Ministry of Labor. The locations of the recruitment sites in our sample are usually construction training schools located in Rajasthan, Punjab, Uttar Pradesh, Bihar, Uttarakhand and West Bengal.[13] At each recruitment site, our enumerators conducted a short baseline survey while workers were waiting for their turn to participate in the job skills test and interview with representatives who traveled from the UAE to conduct the screening for their construction firms.[14] While firms may have a target number of positions to fill in a recruitment round, there is some uncertainty in the number of interviewees who will show up on a given day. Thus, there were times when our enumerator team was unable to baseline all of the workers who appeared at a given recruitment site.[15] In those cases, we conducted the baseline survey via phone within a couple of days of their interview.[16]

All of the positions were in construction work, including job titles such as carpenter, mason, painter, steel fixer and general helper. At the end of the day, the firm's interviewers provided us with a list of people who passed the firm's selection process. Among those who are above the firm's bar for an offer, we randomize five out of seven workers to proceed with the visa and return the list to the firm by the next day. Thus, each recruitment location, date and firm represents its own randomization group. We have a total of 44 randomization groups. The workers were told the next day whether the firm would be making them an offer and proceeding with the visa application or not. Our randomization process was a natural extension of an existing system in which firms request visas from the MOL and sometimes are granted all of them and sometimes fewer than they request.[17] The job interviews and our accompanying baseline surveys happen between August 2016 and May 2017.

The next stage of the process involved the usual medical screening, criminal record

[13]The locations of the recruitment sites are indicated in the red dots in Appendix Figure A.2. The home districts of the workers, shaded by density in the map in Appendix Figures A.2, are usually in the same state or a neighboring state.

[14]We made a slight adjustment to the baseline surveys done in 2017 as compared to 2016 to add questions on assets.

[15]This occurred for 14% of our baseline surveys.

[16]The phone baseline survey was slightly different. It excluded the Ravens-style visual ability test but included a few other questions that were not asked in person.

[17]In our partnership, the construction firms were guaranteed a number of visas in advance but did have to agree to screen more applicants than they usually would need to for every position they wanted to fill.

check and background screening of all visa applicants.[18] The vast majority of workers pass this.[19] Despite not passing this background check, these (few) workers are still counted as treated in our intent-to-treat analyses. The whole process of applying for a visa takes several months, and on average, workers in our treatment group who go to the UAU arrive there work 3.6 months after the job interview.

3.1 Selection

We are interested in two levels of selection. First, are men who apply for contruction jobs in the UAE different from the population of young men in India? Second, are the individuals who fail the screening test different along observable characteristics from the individuals who pass?

In order to assess selection into applications and interviews for these jobs, we compare baseline characteristics of the job applicants in our sample (including those who failed the screening test) with Indian population statistics from the Indian Human Development Survey (IHDS) from 2011-2012 in Table 2. We restrict the IHDS sample to men in our age range and in the states of our analysis. The sample in our analysis has more education with 37% of our survey sample having a high school degree or more as compared with 21% of Indian men. Our sample is lower caste than average, with only one-fifth of our survey sample being general caste as compared with 33% of the IHDS sample. The average annual household income for our analysis group is about 25% lower than the population average. These statistics provide some suggestive evidence that men in India from lower castes may suffer from discrimination in the labor market in India that they may try to escape through international migration.

Next, we compare baseline characteristics of the individuals who pass the screening test by the UAE firms with those who fail in Table 3.[20] The men searching for international jobs average around 28 years old with the workers who fail the interview being slightly older. The failed workers are less likely to have completed high school. About 76% of the analysis sample is Hindu and this is substantially higher (82%) for the failed workers. The failed workers more likely to be lower caste. They also score lower on a Ravens-style test and have higher locus of control. However, they are not statistically different from the workers who pass in their baseline earnings, expectations about their earnings in the UAE, net assets or subjective well-being. In general, workers expect to

[18]The background screening includes checking whether the worker is barred from re-entering the UAE until after a specific date.

[19]Based on a small sample from our second tracking survey, 3.7% of our treatment group did not pass the medical screening, and another 6.9% did not get a visa for other reasons.

[20]Note the number of observations vary across variables because we were unable to administer the visually based Ravens-style ability test for the phone baseline workers, and the question about assets was only added in 2017.

double their annual earnings in the UAE as compared to what their households earn in India.

3.2 Specification

We present our primary results as intent-to-treat estimates. We estimate the following regression, where $Treat_i$ is an indicator for whether individual i got a construction job offer in the UAE at this particular recruitment center:[21]

$$\mathrm{y}_i^{\text{followup}} = \beta \mathrm{Treat}_i + \delta_{FE} + \epsilon_i \tag{1}$$

This equation includes fixed effects for the randomization group, which corresponds with each recruitment day for a particular construction firm.[22] This is necessary as the randomizations are done within these groups. In specifications with additional controls, we also include fixed effects for the enumerator. We examine a number of outcomes, including labor market outcomes, measures of well-being and job amenities. Standard errors are clustered by randomization group.

Appendix Table A.2 shows the summary statistics from the baseline survey for individuals in the treatment and the control groups. For most variables, the two groups are not statistically different from each other at the standard levels. The exception to this is net assets where the treatment group has significantly higher net assets than the control group.

Compliance with the randomization was neither automatic nor complete: treated workers can choose not take the job in the UAE, and control workers can get offers from other UAE firms, or even the same UAE firm later at different recruitment center. Appendix Figure A.3 shows the summary statistics about where the individuals in the treatment and control group ended up at the time of the follow-up survey. About 51% of the treatment group is working in the UAE at the time of the follow-up as compared with 29% in the control group. While the main estimates we show will be intent-to-treat estimates, we will also discuss instrumental variable estimates.

3.3 Handling Attrition at Follow-up

We expected that finding this group of mobile individuals for the follow-up survey would be difficult. Thus, using the contact information from the baseline survey and from the partner firms, we conducted two rounds of phone tracking surveys.[23] We also

[21]There are 65 workers who appear in multiple recruitment sites. For these workers, we define their treatment status by the first time we meet them.

[22]Note while we pre-registered the experiment, we did not pre-specify the regressions or outcome variables.

[23]The timeline for the survey data collection is shown in Appendix Figure A.1. The first phone tracking survey begins four months after we begin our baseline surveys, and the second tracking survey begins six

conducted a phone survey of friends and family using contact information from the baseline to try to obtain updated contact information for the survey.[24] For individuals we could not find via any of these mechanisms and whose baseline addresses were clustered in locations where there were several people we could not follow up with, we sent field teams to physically travel to the addresses that they provided in the baseline survey to find them or their households and get updated contact information on the targeted individual. The follow up survey was conducted via phone from January 2018 to July 2019, and the average time between the baseline survey and follow-up survey is 17.5 months. For workers at our partner construction firms in the UAE, we coordinated with the firms to find appropriate times to talk to the workers.

We show statistics on the percentage of our analysis sample that we followed up with in Figure 1. For some individuals for whom we did not conduct a follow-up survey, we do have additional information about them from either a tracking survey or a friends and family survey. Finally, we also received administrative data on work contracts for anyone in our baseline data from the UAE Ministry of Labor.[25] Thus, for some individuals for whom we do not have data from any post-baseline survey (follow-up, tracking, or friends and family), we do have information about their arrival into the UAE in this administrative data set.

Overall, our attrition rates are similar to or smaller than other comparable studies, but are somewhat imbalanced. Clemens and Tiongson (2017) interview 44% of applicants migrating from Philippines to Korea. Mobarak, Sharif, and Shrestha (2021) interview 68% of their control group and 69% and 94% of their two treatment groups. Gaikwad et. al. (2022) find 63% of their sample in their endline survey. Similarly, we have more attrition in control group than treatment group, and the attriters are different from non-attriters along baseline characteristics.[26]

We do several things to address the issue of attrition. First, for all of the estimates, we also include a specification where we re-weight using the inverse probability of selection into the follow-up, predicted using only baseline characteristics and leaving out individual i in order to obtain unbiased estimates. Appendix Table A.3 shows the baseline variables that predict attrition, and these are the estimates that we use to implement the re-weighting of the estimates for attriters. Second, we make use of administrative data on salaries and compensation of workers in our sample who are in the UAE. Finally, we conduct bounding exercises for our main results.

months after that.

[24] We only conducted the friends and family survey for the subset of workers we could not easily reach using phone numbers from the baseline and tracking surveys or through coordination with our partner firms.

[25] This was matched into our sample using passport numbers based starting a labor contract in the UAE after the start of our experiment and before Fall 2017 (when we received the administrative data).

[26] See Appendix Table A.1.

4 Main Results

4.1 Impact on Working in the UAE

In Table 4, we first examine the impact of being randomly chosen to receive the job offer on the probability that the individual is in the UAE at the time of the follow up. Given that migration to the UAE is predominantly legal migration with a work visa, living in the UAE corresponds to having a job in the UAE. The table is formatted so that each row represents two regressions. In the first column, we show the coefficient on treatment in the parsimonious specification where the only controls are the randomization groups. In the second column, we show the corresponding coefficient in the regression where we include the additional controls for enumerator as well as the re-weighting for attrition. The estimates show that the randomization did increase the probability that the individual in India was in the UAE at the time of the follow-up by 29 percentage points in the parsimonious specification and 24 percentage points with the additional controls and re-weighting. Both estimates are significant at the 1% level, and the magnitude represents more than a doubling of the rate of migration to the UAE relative to the control group. The results indicate that the randomization was successful in generating a first stage by moving people to the UAE. Furthermore, the estimates provide an approximate scaling for the subsequent intention-to-treat results. The intention-to-treat estimates can be multiplied by about three or four in order to get estimates of treatment on the treated.

The next row shows the same outcome of whether the person is in the UAE but the expanded sample includes individuals for whom we did not conduct a follow-up survey but we have other data including the friends and family surveys and the administrative data from the MOL to determine whether they went to the UAE or not. The treatment effects remain positive and significant at the 1% level but the magnitudes here are slightly smaller. The third row shows the length of time in the UAE since randomization, where those still in India are given zero, we find that the treated workers have spent on average 3.4 months longer in the UAE.

In the fourth row of the table, we also look at a question in the follow up survey that asks whether the respondent is currently residing in their home district. This indicator will equal zero for all individuals who are in the UAE but it will also equal zero for anyone who is working and living in India but outside their home district at the time of the follow up survey. In the parsimonious specification, we see the treatment group is 20 percentage points less likely to be residing in their home district in India at the time of the follow-up survey. This drops to 15 percentage points with the additional controls and weights. Both estimates are significant at the 1% level. These estimates are smaller in magnitude than the impact of going to the UAE, suggesting that the control group is more likely to have migrated within India than the treatment group.

Finally, in the last row, we look at the type of job that the person is working in. While most of the control group are working in construction, the impact of getting the UAE job offer increases the probability that a person is in the construction industry by 13 to 14 percentage points. These estimates are significant at the 1% level.

4.2 Impacts on Labor Market Outcomes

We next look at the impact of randomly receiving the offer on the men's labor market outcomes in Table 5. We begin with total compensation which includes earnings and the value of housing and food provided by the employer which are the two main categories of in-kind benefits that workers in the UAE commonly receive. This market value of these two in-kind benefits are specified in the employment contract, so workers have a good idea of these numbers. The measure is the total compensation per month in thousands of rupees.[27] The total monthly compensation of the treated individuals are 5170 INR higher than in the control group in the parsimonious specification and 4480 higher with the additional controls and weights. Both estimates are significant at the 1% level. The intention-to-treat estimate here represents a 26% to 30% increase in compensation relative to the control mean.[28]

It is unclear whether the workers value the in-kind benefits of housing and food at the market value reported given that it should be much cheaper for them to live and eat at home in India. Thus, we also look at a measure of average monthly earnings in the past year that includes only their take-home earnings and excludes the value of any employer-provided benefits. Using this measure, the treatment group is earning 2760 to 3020 INR more than the control group. This difference represents an ITT of 19% to 21%. These estimates are also significant at the 1% level. In addition to the regression estimates, Figure 2 shows that the distribution of earnings and compensation shifts clearly to the right for the treatment group relative to the control group.

Getting the visa and offer in the UAE also decreases the probability that the men are unemployed by 4 to 7 percentage points. Note that the parsimonious estimate is significant at the 5% level but the estimate with additional controls and weights is only significant at the 11.7% level. While the rate of unemployment in the control group is 21%, getting the offer in the UAE reduces the probability that workers in the treatment group are unemployed by 18 to 31%.

Given that a substantial number of people in the sample are unemployed (and

[27]The responses in other currency, mainly dirham, are converted to rupees using an exchange rate for the midpoint of our follow-up data (October 2018) from the IMF.

[28]Appendix Table A.5 shows the corresponding instrumental variables estimates of treatment on the treated. The magnitudes of the IV estimates correspond to scaling the intention-to-treat estimates by about three times.

do not report earnings), we also look at a measure of total compensation and monthly earnings where we fill in missing values of earnings with zero for individuals that report being unemployed and do not respond to the question about earnings. The magnitude of the estimates are slightly larger and are significant at the 1% level.

The treatment group is earning more but also working 2.91 to 4.05 more hours per week than the control group (significant at the 1% level). On average, workers in the control group work 54.2 hours per week, so this represents an increase of about 5 to 7%. Thus, if we were to adjust the earnings impacts to an hourly wage, the treatment would have a positive impact on hourly wages. Regarding hours, we also asked in the follow-up survey their preference for more or less hours of work. Most workers (63%) in the control group would prefer more hours.[29] There is no statistical difference for the treatment group on this preference despite the fact that the treatment group is working substantially more hours.[30] This provides some evidence against the idea that migrants workers in the GCC are being forced to work excessive hours as represented in some media reports (e.g. McQue 2022).

Finally, we look at the impact of treatment on the amount of time that individuals spend commuting one-way per day. Average commute times are not trivial for the control group where a one-way commute takes 35 minutes. The estimates for the treatment group suggest that their commutes are one minute shorter, though this difference is not statistically different at the standard levels. Dormitory compounds for migrant workers in the UAE tend to be located substantially outside of the city centers and they are bussed into the city for construction jobs.

While all of the estimates discussed so far on labor market outcomes (in Panel A of Table 5) make use of only our follow-up survey data, we also consider the impacts on earnings and compensation using the additional administrative data that we have from the MOL for the workers in the UAE. Specifically, the administrative data set includes information specified in the contract between the worker and the firm on monthly earnings, and the value of food of housing provided by the employer. Thus, we can use this MOL contract salary to impute average earnings and total compensation for workers who are in the UAE but for whom we do not have follow-up survey data.

As discussed in Joseph, Nyarko and Wang (2018), the contract salary specified in the MOL is a lower bound base salary where workers often earn more than that amount depending on the overtime hours that they work. Thus, we first estimate the relationship between contract salary and contract compensation (including the value of in-kind benefits) in the MOL and reported earnings and compensation in

[29] On average in the control group, 3.6% would prefer less hours and the remaining 33% would prefer the same number of hours.

[30] The magnitude of the coefficient is also close to zero.

the survey data for individuals for whom we have both data.[31] Then, we take the coefficient estimates and combine it with the MOL contract salary and compensation to impute earnings and compensation values, respectively, for individuals for whom we are missing follow-up data. As shown in Panel B of Table 5, the range around the coefficient estimates when we expand the sample to include these imputed values of the dependent variable are very similar to the estimates without the imputations.[32] These results provide additional support against the idea that our findings are driven by attrition.

4.2.1 Expectations at Baseline

One concern that arises regarding migration is whether they have the right expectations regarding the returns to migration at the time that they are making their decision. Numerous stories abound documenting unscrupulous practices by labor intermediaries who promise jobs with higher salaries or better conditions and benefits that are actually not accurate, leading to migrants feeling deceived.[33] In this particular context, this can also arise not through direct dishonesty but because migrants are given a contract with a base salary but they expect to get overtime hours beyond their base salary with overtime pay at a higher wage rate.

We compute the difference between how much they expected to earn in the UAE at the time of the baseline survey in India with how much they are actually earning at the time of the follow-up survey. Figure 4 shows the log difference between their actual earnings in the follow-up survey with the amount that they said that they expected to earn prior to migration for those in the UAE (in the solid black line) as compared to those in India (in the dashed grey line). For those in the UAE, the distribution of the difference between what they expected to earn and what they are actually earning in the UAE is centered around zero. The mean log difference is -6.3%, so the average worker is earning a little less than expected.

For those in India at the time of the follow-up survey, the dotted grey line gives the difference between how much they expected to earn in the UAE at baseline and how much they are earning in India. They are earning less in India than they expected to earn if they migrated, consistent with the idea that they only migrate for higher earnings. The mean difference for those in India is -73%. Thus, the sample in India at the follow-up are earning 73% less than they expected to earn in the UAE at baseline, but for the sub-sample who are in India at the time of the follow up survey, a gain of

[31] The estimates are shown in Appendix Table A.4.

[32] Interestingly, the estimates from the parsimonious specification have smaller magnitudes than the estimates with the weights and additional controls, but the implied range from the coefficients is very similar.

[33] For specific anecdotes, see for example Auwal 2010.

73% is not enough to induce them to migrate on average as their reservation earnings for migration require 87.8% higher earnings.[34]

4.3 Impacts on Well-Being and Work Satisfaction

While we have demonstrated that Indian men earn substantially more in the UAE than in India, we are interested in the broader impacts of migration on the well-being and work amenities of individuals. We ask a set of 8 standard questions on well-being about how often did they experience the following feelings in the last month: stress, worry, anger, sadness, pain, loneliness, enjoyment, happiness. They respond on a 3 point scale: rarely, sometimes, often. We convert this to a single index of well-being that is a standardized weighted index with a mean of 0 and a standard deviation of 1.[35] First, Panel A of Figure 5 shows the density functions for the index of well-being for the treatment group and the control group. We can see a clear shift to the left in the distribution of well-being for the treatment group relative to the control. In these distributions, the treatment effect is a decline in 16% of a standard deviation for treated relative to control.

We also show the impacts in the regressions with additional controls in Panel C of Table 5. In the parsimonious specification, we see a 16% decline in well-being of the treatment group relative to the control group. This is significant at the 1% level. With additional controls and weights, the magnitude of the coefficient drops to 13% (significant at the 1% level).

We show the impacts on each of the individual components of the well-being index in Panel A of Figure 6. The components are all standardized so that negative coefficient values correspond with being worse off. The largest change in terms of magnitude is the increase in physical pain (and this estimate is significant at the 5% level). While many of the components have negative coefficients, the only other component that is statistically significant is enjoyment with the treatment group experiencing less enjoyment than the treatment group.

We also ask a set of standard question on work satisfaction on a five point scale from strongly agree to strongly disagree. They are asked about climate at their workplace, the risk of accidents, health hazards at work, supervisor providing encouragement, control over work hours, physical effort, opportunity for promotion, fighting and bickering at work, supervisor unfairness, whether the person would recommend this job to their friends, uncertainty in their workload. As with well-being, we create a similar standardized index across these measures.

[34] This is based on a survey question we asked at follow-up about the reservation earnings needed for those in India to migrate to the UAE.

[35] We use a GLS weighting procedure that down weights the components that are highly correlated with other components to maximize the independent contribution of each component.

Panel B of Figure 5 shows the density functions for the index of work satisfaction for the treatment and control groups. The mean of the distributions are very similar though there is a bit more dispersion in the treatment group than in the control group. The coefficient estimates from the regressions (shown in the last row of Table 5) are not statistically different from zero. While media reports on migrant working in the Gulf focus on poor working conditions (e.g. McQue 2022), our results indicate that overall working conditions in India are similarly poor.

The regression coefficients for each of the components of work satisfaction are shown in Panel B of Figure 6. These are presented so that positive estimates mean better outcomes. While there is no effect on the summary index of work satisfaction, there is a positive effect on some components and a negative effect on other components. The treatment group reports significant increases in physical effort needed for the job. This may correspond to them feeling more physical pain (Panel A of Figure 5). There is also significantly worse climate on the job in the UAE, consistent with a lot of construction work being outdoors and higher temperatures in UAE than in India. However, migrant workers to the UAE are significantly better off in terms of less accident risk, having more encouraging supervisors, and having supervisors who are fairer to them.

Thus, while they are earning much more in the UAE, these men are experiencing substantial declines in their short-run general well-being in the UAE. They have more physical pain, and this corresponds to the construction jobs in the UAE requiring more physical effort, as well as the higher temperatures the construction workers bear in the UAE. They also experience significantly lower enjoyment and happiness, and, consistent with the more diverse friendships and co-workers we discuss below, they are more likely to report loneliness (though the estimate on loneliness is not statistically significant).

4.4 Bounding for Attrition on Main Results

We have so far discussed results from two approaches to the problem of attrition: re-weighting and using data from sources other than the follow-up survey. We also implement attrition bounds that imputes outcomes for attritors (Manski 1989). First, for the upper-bound estimate, we assume the attritors are 25% of a standard deviation above the mean for the treatment group and 25% of a standard deviation below for the control group. Next, we generate a lower-bound where we assume the attritors are 25% of a standard deviation below the mean for the treatment group and 25% of standard deviation above for the control group. This approach assumes that the attritors in the treatment and control group behave differently in such a way that creates the widest possible bounds. The mean and standard deviation that we use in these calculations are calculated differently based on whether they are in the UAE or not and whether they are in the treatment group or not. This takes advantage of the fact that we have more information than in most cases of attrition because we have administrative data from the UAE MOL on whether the individual in the sample made it into the UAE, and allows us to generate tighter, location-specific bounds.

Table 6 shows corresponding lower-bound and upper-bound estimates of the key labor market and well-being outcomes. While the magnitudes of the coefficients mechanically must change as a result of this exercise, it is reassuring to see that all of the results on total compensation and earnings (in Panels A and B) remain positive and significant at the 1% level even with the relatively strong assumptions associated with the bounding exercise. While the lower-bound estimate for work hours is no longer significant at the standard levels, the direction of the effect on hours remains.

One result that is more sensitive to the worst-case scenario assumptions about the attritors is the well-being index. The upper-bound estimate on well-being (in Panel C) is no longer negative. However, this upper-bound estimate is also not significantly different from zero, so we cannot reject that it is actually negative. To explore the sensitivity of the estimates on well-being to the assumptions on attritors further, in Figure 7, we look at assumptions where we assume attritors are different fractions of a standard deviation above and below the mean rather than just the 25% fraction that are presented in Table 6. The results in Figure is somewhat reassuring in that we can see that the results on the well-being index are robust to a slightly lower fraction above the mean. The bounding estimates are robust if we assume that all attritors are 10% of a standard deviation above or below the mean. The upper bound on the coefficient estimate is negative(but not significant) when we assume attritors are more than 15% of a standard deviation above/below the mean.

4.5 Impacts on Financial Outcomes

In Table 7, we first look at the impact on net assets (which is the value of various components of household assets less their total debt). Those offered a job in the UAE tend to have fewer net assets but this is not statistically significant at the standard levels.[36] We look separately at whether the UAE job offer affects total debt in the second row. We do see an increase in debt of 6390 INR in the parsimonious specification, and this estimate is significant at the 10% level. This represents a 19 percent increase in debt relative to the control mean. The coefficient is slightly smaller with the additional controls and weighting, leading the estimate to only be significant at the 17% level. The increase in debt is consistent with the idea that those offered a job in the UAE

[36] Appendix Figure A.4 shows the estimates for each component of total assets. There is a significant increase in informal debt for the treatment group relative to the control group and a significant decline in the value of vehicle assets.

went into debt in order to finance the payment of the labor intermediary fee and still have higher levels of debt at the time of follow-up.

As expected, those offered a job in the UAE remit more to their families at home. They remit on average 4020 INR more than those who did not receive a UAE job offer in the parsimonious specification and 4030 INR more with additional controls. Both estimates are significant at the 1% level. The estimates also suggest that workers in the UAE are remitting a very substantial share of their cash earnings to their families at home in India.

Finally, we look at the amount that the individual have paid in labor intermediary fees for the international job placement. Those offered a UAE job in our experiment paid between 12,450 to 14,370 INR more than those not offered the job in our experiment, and these estimates are significant at the 1% level. Assuming that the intermediary fee effect is amortized over the expected duration of the migration spell, this amounts to roughly 440 INR a month.[37] Adding this sum to the remittance amount, we can almost fully account for the total compensation gain from getting an offer: the gains almost all accrue to the household, with roughly 9-12% going to labor intermediaries and moneylenders. Given that total assets of the households show no gain at the time of the follow-up survey, the results suggest that treated households are spending the remittances that they receive on consumption, education, or other expenditures that do not generate additional assets in the short run.

4.6 Impacts on Attitudes and Social Networks

In addition to how international migration affects the earnings, financial status and broader well-being of individuals, we consider how the experience of international migration alters people's social groups and their attitudes about labor markets and politics. Broadly, we are interested in whether international migration produces new experiences and interactions with people whom migrants may not have interacted with before, changing social networks. Further, we are interested in whether the experience of migration may change people's attitudes about the world, their host and source countries, and people from other linguistic and religious backgrounds.

First, we ask all survey participants whether they agree with the statement that people are rewarded for effort, intelligence and skill in India and in the UAE in two separate questions. The responses are recorded on a five point scale where 1 corresponds to strongly agree and 5 to strongly disagree, but we convert the measure to a binary

[37] This calculation uses the average expected duration in the UAE reported at baseline of 32 months and assumes no discounting. If we take into account discounting associated with the fact that the agent fee is paid upfront prior to migration and assume a 2% monthly interest rate, this number increases to 612 INR per month.

value of whether the respondent picked an option above the median. This allows us to examine whether the experience of international migration shifts what people think about whether people are rewarded for the kinds of things that we think well-functioning labor markets should reward people for including working hard, intelligence and having skills in their home country and in the destination country.

As shown in Panel A of Table 8, getting a job offer in the UAE increases the probability that people think you are more rewarded for effort, intelligence and skill in India. This estimate is significant at the 1% level in the parsimonious specification and at the 12% level with the additional controls and weighting. There is no significant effect of the job offer on their assessment of the returns to effort, intelligence and skill in the UAE. This suggests that the experience of working and living in the UAE shifts attitudes of Indian men towards thinking that India is relatively more meritocratic than the UAE. Thus, while they earn much more in the UAE than in India, Indian workers in the UAE are more likely to think that effort is rewarded in India.

We also ask respondents whether they think differences in income are too large within India and within the UAE and convert the five point scale to an indicator above median value. We are interested in capturing how their attitudes towards income inequality may change as a result of international migration. While the individuals in our sample are from households earn considerably less than the average in India (as shown in Table 2), they are not at the very bottom of the income distribution in India. In contrast, while Indian workers enjoy a higher level of earnings in the UAE, they are considerably lower in the income distribution in the UAE. Thus, one mechanism for a change in attitudes about income inequality can be driven by the experience of living in a place with different levels of inequality or the experience of being in a different point in the distribution. An alternative mechanism is that their attitudes about inequality change as a result of earning more vis-a-vis others in India. The estimates in Panel A of Table 8 suggest that being offered a job in the UAE corresponds with a decline in their assessment of the income gap being too large in India and an increase in feeling that the income gap is too large in the UAE. However, these two outcomes are sensitive to the specification and only significant at the 1% level with one set of controls. The results on attitudes about the income gap in India are similar to the findings of a concurrent working paper (Gaikwad, Hanson and Toth 2022) that finds that migration to the Gulf leads Indians to reduce their support for government redistribution.

We also ask the respondents to rate their feelings towards Indian Hindus and Indian Muslims using a feeling thermometer that has a scale that ranges between 0 and 100.[38] There has been some conflict across religious groups in India. We construct the variable

[38] We explicitly explain that ratings between 50 and 100 are favorable and warm towards the group while ratings from 0 to 50 are unfavorable.

as how they rate the Indian in the religion that is not the one that they belong to. The control group is solidly favorable towards those in the other religion with an average rating of 72.5. Their feelings towards the other religious group increases with international migration. As shown in Table 8 Panel A, the magnitude of the impact of the intention-to-treat estimate is 2.7 in the parsimonious specification and 3.3 with the additional controls and weights but only the latter is significant at the 5% level. This suggests that exposure to different groups that accompanies international migration corresponds with a more favorable view of other groups.

We also ask about the way our sample feels about Emiratis (citizens of the UAE). Overall, the control group feels favorable towards them and assesses their feelings at 73.2.[39] In the parsimonious specification, we see that being offered a job in the UAE corresponds with a 2.8 degree increase their feelings about Emiratis (and this is significant at the 10% level). However, both the magnitude of the estimates and significance drop with the inclusion of the additional controls and weights.

Next, we are interested in whether the way that Indian view democracy changes as a result of their move from their democratic home country to an authoritarian country. They may be less favorable towards democracy if they have a positive experience of living in an authoritarian country that has been economically successful. Alternatively, they may be more favorable towards democracy if they dislike the experience of lacking political voice in the authoritarian country. Specifically, in the follow-up survey, we ask how important it is for the respondent to live in a country that is governed democratically. We offer a scale from 1 to 10 where 1 corresponds to not at all important and 10 to absolutely important. The average answer in the control group is high at 8.81 out of 10. The coefficient estimate for those offered jobs in the UAE is positive but small and not statistically different from zero. The lack of impact we find of migration from a democracy to an authoritarian regime on preferences for democracy is also documented in Gaikwad, Hanson and Toth (2022).[40]

We next discuss how friendships change as the result of international migration. In the first row of Panel B, we see that getting an international job offer corresponds with a decrease in the probability that the person's closest friend has the same religion of 3 percentage points in the parsimonious specification. This estimate is significant at the 10% level but loses significance with the additional controls and weights. Similarly, Indian men reduce the probability that their closest friend is of the same caste. This estimate ranges from -6 to -7 percentage points and are significant at the 1% and 5% levels in the parsimonious specification and with additional controls, respectively. In

[39]Interestingly, this is very similar to but slightly higher than the way that they feel towards Indians of a different religion.

[40]This contributes to a broader literature on the impact of international migration on attitudes about politics and democracy (e.g. Careja and Emmenegger 2012).

addition to questions on their closest friends, we also ask a set of questions regarding whether they have any friends who speaks a different language, is from a different religion or is from a different caste. The estimates on these individual measures are sensitive to the specification and not significantly from zero with the additional controls and weights. To summarize these dimensions of a worker's social network, we construct a friends similarity index that combines all of the questions on friends. In the index, we see that getting a job offer in the UAE leads to a significant decline in having friends who are very similar.

While people can choose their own friends, we also consider whether they are exposed to different groups through their work teams or whether work teams in the UAE are organized so that teams are comprised of very similar people. The results in Panel C of Table 8 suggest that migration to the UAE corresponds with working in teams with slightly different people. The share of teammates speaking the same language declines by about 3 percentage points (significant at the 5% level). While there is no significant change in the share of teammates that have the same religion, the team similarity index that incorporates both the language and religion measures is negative and significant at the 5% level. Finally, being offered a job in the UAE has no significant impact on the size of work teams.

Overall, the results suggest that migration to the UAE exposes these men to different people than they would associate with in India. They work with more diverse teams and choose friends, including best friends, who are more different from them. Corresponding to increased exposure to different groups of people, we see that being offered the opportunity to migrate to the UAE corresponds to having more positive opinions of people of other religions and emiratis. Our findings correspond with the existing literature that demonstrates that exposure on sports teams (Lowe 2021) and in classrooms (Rao 2019) reduces prejudice against other groups and facilitates intergroup friendships. Other attitudes change as well, including views on income inequality and what is rewarded in the labor market in India. However, migration does not significantly change their attitudes about the importance of democracy.

4.7 Heterogeneity

4.7.1 Heterogeneity by Observables

We begin by looking at heterogeneity in the effects of the UAE job offer by observable characteristics of the individual at baseline.[41] In Panel A of Figure 8, we look at the outcome of migrating to the UAE. This provides us with insight into whether the

[41] The indicators for married and having kids are based on survey questions at follow-up but we are able to construct whether they were married or had children at the time of follow-up using questions about the year of marriage and the age of their children.

migration decision varies by observable characteristics among those who received a job offer in the UAE from our randomization. For baseline variables that are continuous or categorical, we convert them into indicators for above the median value and interact those indicators with the treatment variable. The figure shows the coefficient estimates of the interaction between the indicator and treatment. For most variables, there is no significant heterogeniety in take-up of the offer to migrate. The exception is higher levels of happiness at baseline. This is significant at the 10% level. The result emphasizes that well-being is not just an outcome that changes with migration (as we have shown) but people's state of mind is also an important determinant of the decision to migrate.

Next, we look heterogeneity in these estimates when the outcome is total compensation in Panel B of Figure 8. Again, most of the estimates are not significantly different from zero at the standard levels. Those with prior work experience in the UAE earn substantially and significantly more when offered a new job in the UAE. Individuals who have higher household income at baseline, are also significantly more likely to earn more when offered a job in the UAE. This coefficient is significant at the 10% level. However, this does not seem to capture a correlation between baseline income and education or cognitive ability because the interactions of the treatment effect and education or ability are not significantly different from zero. In fact, the coefficient on the interaction of treatment and more education is negative. Thus, the results suggest that while workers earn more in the UAE, there are not higher returns to education or cognitive ability in the UAE as compared with India.

Finally, in Panel C of Figure 8, we look at heterogeneity in the treatment effects on well-being. For this outcome, only one variable is significantly different from zero at the standard levels. Individuals who have previously migrated to the UAE have much higher levels of well-being when offered another job in the UAE. This is likely driven by selection: individuals who were happy with their prior experience in the UAE are the ones who are likely to return.

4.7.2 Heterogeneity by Unobservables: Marginal Treatment Effects

In this section, we build on marginal treatment effects (MTE) in models of self-selection developed in the literature (Brinch, Mogstad, and Wisvall 2017, Kowalski 2020, Heckman and Vytlacil 2006). The empirical model has potential workers with unobserved tastes for staying home (or distaste for migrating), denoted U^D. A high value of U^D implies a worker has a high value of staying in India, and a low value of U^D implies a worker has a low value of staying in India. This is utility that is independent of the instrument denoted by Z, which is the randomized offer. So the total unobserved utility of migrating for individual i is given by:

$$\gamma Z_i - U_i^D \tag{2}$$

where $\gamma > 0$ is a parameter converting the randomized offer variable Z_i into utility for migration. This is a reduced form representation including various types of search frictions that impede getting a guest-worker offer, which are reduced by the randomized offer. The monotonicity assumption ensures that randomly receiving the job offer in the UAE makes the value of going to the UAE higher by reducing the cost. Given costs and benefits, an individual migrates ($D_i = 1$) if the benefits minus costs, including the unobserved disamenity of migrating, are greater than 0:

$$D_i = 1 \iff B_i^{UAE} - B_i^{India} - (C_i^{UAE} - C_i^{India}) - U_i^D + \gamma Z_i > 0 \tag{3}$$

where the benefits of each location $k \in \{India, UAE\}$ are denoted B^k and costs are denoted C^k. The randomization assumption guarantees that $Z \perp B^{UAE}$, C^{UAE}, B^{India}, C^{India}, U^D, but allows arbitrary correlations between $B^{UAE}, C^{UAE}, B^{India}, C^{India}$ and U_D. The first-stage regression of D_i on Z_i recovers an estimate of γ.

We write the net observable benefit of migrating (in a money metric) to location k as $Y^k = B^k - C^k$. Given the lack of heterogeneity on observables, except for previous experience in the UAE, we focus on the marginal treatment effect that is solely a function of the latent distaste for guest-worker migration U^D, and return to heterogeneity on observables in the next subsection. We have:

$$MTE(u) = E[Y^{UAE} - Y^{India} | U^D = u]. \tag{4}$$

The MTE in a money metric is the comprehensive return to migrating to the UAE, including both costs and benefits, so long as both are observed. An alternative interpretation of the MTE is the willingness to pay for guest-worker migration given a latent preference over staying home. The main constraint on estimating the MTE is the lack of variation in Z sufficient to trace out a non-parametric treatment response function. However, in the case with a binary instrument and binary endogenous variable, we can recover a linear MTE function, as in Brinch et al. (2017). Note that monotonicity means that never-takers (who received the randomized offers but did not migrate) must have higher U^D than treated compliers (who got offers and migrated), and never-takers must have lower U^D than untreated compliers (who did not get an offer and stayed in India).

In Figure 9, we plot the average outcomes derived from the marginal treatment effects in the solid lines where U^D is on the horizontal axis. The figure shows the outcomes for always-takers and never-takers, and compliers in the UAE and in India. The difference between the migrant and non-migrant compliers gives the LATE, averaged over the randomization groups. The always-takers in the UAE are defined as individuals in the control group who migrate to the UAE despite not having received an offer in our experiment. They have the lowest taste for staying in India (U^D). The never-takers in India are individuals in the treatment group who stayed in India rather than taking the offer to migrate. Under the Roy model interpretation, this group must have the highest taste for staying in India (U^D). Then there are two groups of compliers: those who received the offer (i.e. the treatment group) and chose to migrate to the UAE and those who did not receive the offer (i.e. the control group) and choose to stay in India. The threshold $p_L = Pr(D = 1|Z = 0)$ corresponds to the share of people who did not get the offer and still went to the UAE, while $p_H = Pr(D = 1)$ is the share of people who migrated.[42]

Without any other assumptions, we can already see that the "untreated outcome test" proposed by Kowalski (2020) reveals little selection into treatment on the basis of either well-being or total compensation in India because the never-takers have outcomes in India that are very similar to the untreated compliers. Consistent with this, Appendix Table A.6 shows that the only significant difference between compliers and never-takers out of 13 baseline characteristics is happiness. However, compliers can still differ from never-takers on the basis of outcomes in the UAE, but these outcomes are not possible to estimate without further assumptions.

The most transparent assumption is that the marginal treatment effect is a linear function of U^D. Under the assumption of a linear MTE, the potential outcomes for the never-takers and always-takers can be extrapolated (Brinch et al. 2017), as shown in the dashed lines in Figure 9. A linear MTE implies that the outcomes from staying in India for the always-takers can be computed from linearly extrapolating the Y^{India} for the untreated compliers and the never-takers. Similarly the outcome of going to the UAE can be imputed for the never-takers from the observed Y^{UAE} for the always-takers and the treated compliers.

In Panel A of Figure 9, we see that the never-takers have lower potential Y^{UAE}, measured as total compensation, than the compliers in the UAE or the always-takers. As previously noted, there is very little heterogeneity in potential Y^{India} among the

[42] In terms of observables, the always-taker mean outcomes plotted are $E[Y^{UAE}|D = 1, Z = 0]$, the never-taker means are $E[Y^{India}|D = 0, Z = 1]$, and the complier mean in the UAE is

$$\frac{p_H E[Y^{UAE}|D = 1, Z = 1] - p_L E[Y^{UAE}|D = 1, Z = 0]}{p_H - p_L}$$

while the complier mean in India is given by

$$\frac{(1 - p_L)E[Y^{India}|D = 0, Z = 0] - (1 - p_H)E[Y^{India}|D = 0, Z = 1]}{p_H - p_L}$$

.

various groups, meaning that all of the heterogeneity in the MTE (under the linear assumption) is coming from heterogeneous returns in the UAE. Panel A of Figure 9 suggests that while never-takers have lower returns to migration than compliers or always-takers, the marginal treatment effect of the UAE guest worker program are still large, positive, and significant for them, so the large rates of non-compliance implies strong tastes for staying in India.

The presence of strong tastes for staying in India is consistent with the results on well-being. In Panel B of Figure 9, we see that always-takers have much higher well-being than compliers in the UAE (and this difference is significant at the 10% level). For always-takers, they have much higher levels of well-being than the treatment group of compliers in the UAE though they earn on average a little less. This result implies that the always-takers have a much smaller fall in well-being than the LATE implied by the compliers, and the LATE on well-being is smaller than the extrapolated effect on never-takers. Together Panel A and Panel B of Figure 9 shows that the heterogeneity is such that the workers who do not want to migrate (i.e. have the higher U^D) may have the lowest pecuniary returns, but also suffer the largest non-pecuniary costs, as proxied by falls in well-being.

If we take the marginal treatment effects on well-being for never-takers as a summary measure of the non-pecuniary costs of these jobs, we can calculate that never-taker workers are willing to give up roughly INR 15,000 per month, or 150% of Indian earnings of the never-takers, in exchange for one standard deviation gain in well-being. This magnitude is substantially larger than other estimates of the pecuniary value of a standard deviation of subjective well-being, which are on the order of 20-50% increases in income (Cesarini et al. 2020, Deaton and Stone 2013). This suggests that either our subjective well-being measure is not capturing all the disamenities of the job or that our population has a higher marginal rate of substitution between well-being and income.

Given that our sample is drawn from the population in India who are interviewing for jobs in the UAE, these estimates may be a lower bound on the non-pecuniary costs of guest work in the UAE relative to work in India. We can further examine the external validity of our sample by looking at the observable differences between the compliers, always- and never-takers and the workers rejected by the firm screening. In Appendix Table A.6, we can see that all of the groups in the experimental sample have higher education and ability than the rejected, suggesting that the returns to migration may be even lower for those screened out by the skills test.

4.7.3 Evidence from Reservation Earnings

We can obtain another estimate the non-pecuniary costs of migration by using questions about reservation wages. At the time of the follow-up survey, we ask a question about the minimum earnings that they would accept to switch locations. In other, words, for individual in the UAE, we ask the minimum amount that they would accept to return to India, and for those currently in India, we ask the minimum amount that they would accept to induce them to migrate temporarily to the UAE. The difference between the wages of the UAE workers and their Indian reservation wages measures the disamenity costs of migration from India to the UAE. For comparison, we also asked Indian workers the lowest wage they would take to migrate to the UAE, which would recover both the any fixed costs of migration as well as the disamenity. If workers reported reservation wages in the UAE above their current Indian wages, this is driven by the disamenities of migration to the UAE.

Formally, if the UAE workers are making Y^{UAE}, and report the wage R^{India} that would make them indifferent, with U_i^D being the non-pecuniary cost of migration, then $Y_i^{UAE} = R_i^{India} + U_i^D$ and similarly $Y_i^{India} = R_i^{UAE} - U_i^D$. Among first-time migrants who are in the UAE (and thus have paid the fixed costs), the taste for staying in India is $U_i^D = Y_i^{UAE} - R_i^{India}$ for workers in the UAE and $U_i^D = R_i^{UAE} - Y_i^{India} - F$ for workers in India.

Figure 3 shows the distribution of the difference between log reservation earnings and log current earnings, separately for those in India (in the dotted grey line) and the difference between log current earnings and log reservation earnings in the UAE (in the solid black line).[43] For those in India, on average they need at least 87.8% higher earnings to induce them to migrate. Interestingly, this number is in the ballpark of the percentage returns we actually see associated with migration in the IV estimates (Appendix Table A.5). It is also noteworthy that the amount needed to induce migration to the UAE is not symmetric to the amount required by those in the UAE to return to India, consistent with the prediction of the fixed cost of migration. Those in the UAE could return to India for 20% lower earnings than what they are currently getting.

5 Conclusion

Our paper presents results from the first randomized experiment evaluating the impact of guest worker programs on the outcomes of the workers. Consistent with past research, we find large and significant positive effects on earnings and income for workers given an offer. Including the value of in-kind benefits, we estimate gross returns of

[43]This corresponds to U_i^D. The distribution of the reservation earnings alone (not differenced with current earnings) are shown in Appendix Figure A.5.

INR 4700 to INR 5900. These returns are reduced by 10-15% once we account for the substantial fees charged by labor market intermediaries.

Despite the large average returns to migration to the UAE, we have significant non-compliance with the experimental job offer, with around half of the treatment group not migrating to the UAE. We find evidence of selection on unobserved tastes for migration to the UAE. This interpretation is also consistent with our estimates showing significant negative effects of migration on the well-being of migrants.

The presence of unobserved heterogeneity in tastes for migration belies views of guest program programs that implicitly assume a fully elastic supply of potential migrants. Proponents of guest worker programs as a pathway out of poverty often assume that workers in poor countries have a high demand for guest worker jobs, but visa limitations prevent more individuals from developing countries from migrating. Our evidence suggests that the near doubling of earnings associated with this kind of migration is still not enough to induce migration among the pool of individuals offered the opportunity. Our research suggests that there is a large loss in individuals' well-being associated with these moves. However, in contrast to the way the media represents guest worker jobs in the GCC (e.g. McQue 2022, Human Rights Watch 2017), the lower levels of well-being are *not* driven by poor working conditions or excessive work hours as we find work satisfaction and the desire for more hours to be similar in our treatment and control groups. Thus, many individuals in poor countries are not willing to give up their lives in their home countries for much higher wages in the GCC. Whether or not this implies that guest worker programs have limits on their scalability we leave as a question for further research.

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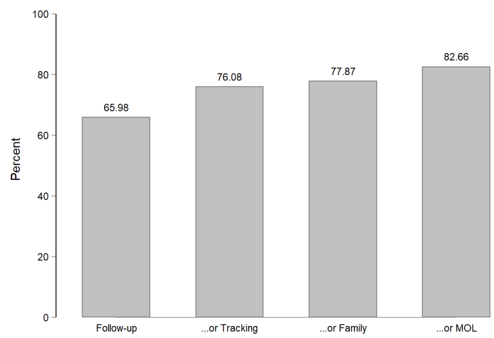
6 Figures

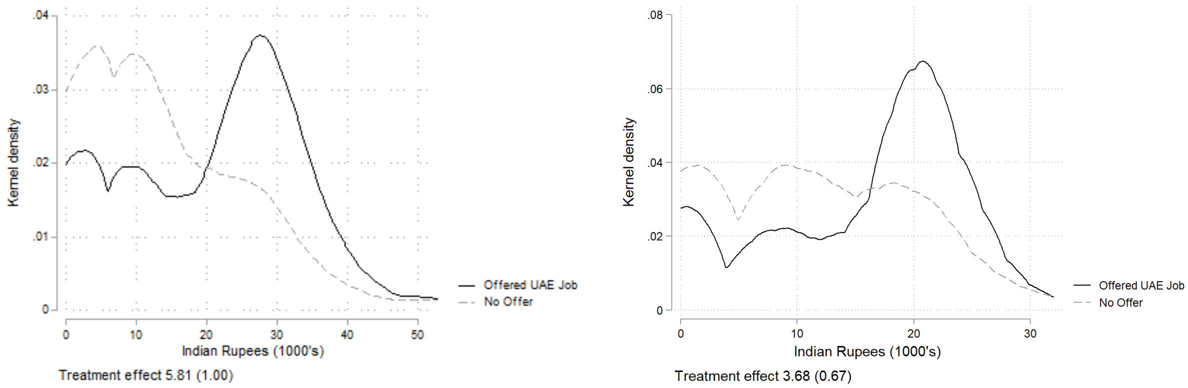
Figure 1: Rates of Follow-Up



Notes: This shows the percent of people from the baseline analysis sample for which we have either the follow-up survey data or data from another source (tracking surveys, family survey, MOL administrative data) where each source progressively adds more information.

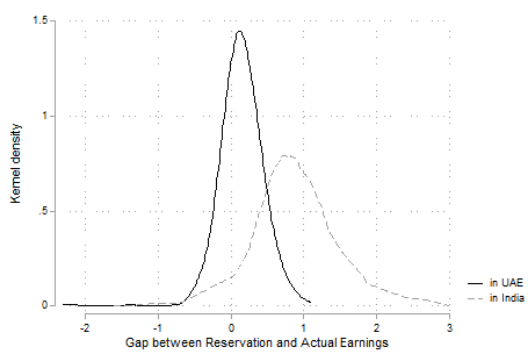
Figure 2: Distribution of Earnings and Compensation by Treatment Status

(a) Total Compensation **(b)** Monthly Earnings



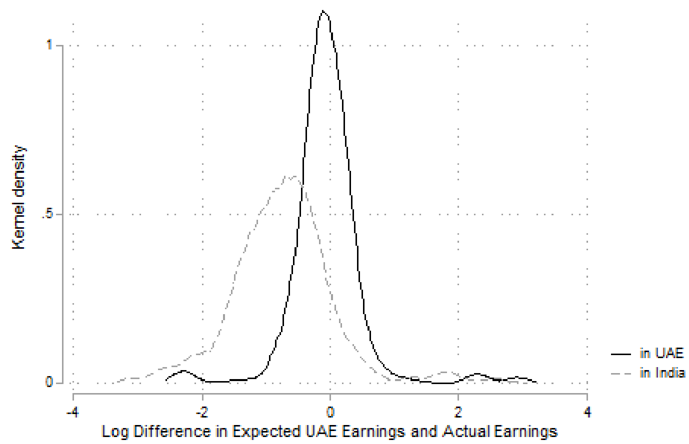
Notes: The figures show the distributions of the variables using kernel density functions. Each variable is shown separately for the treatment group and the control group.

Figure 3: Distribution of Disamenity from Being a Guest Worker in the UAE by Current Country of Residence



Notes: The figures show the distributions of the gap between the logarithm of reservation earnings (to move to the other location) and the logarithm of current earnings using kernel density functions. In the UAE, this is log reservation earnings (to move to India) minus log actual earnings in the UAE. In India, this is log actual earnings In India minus log reservation earnings (to move to the UAE).

Figure 4: Distribution of the Gap between Expected UAE Earnings and Actual Earnings by Current Country of Residence

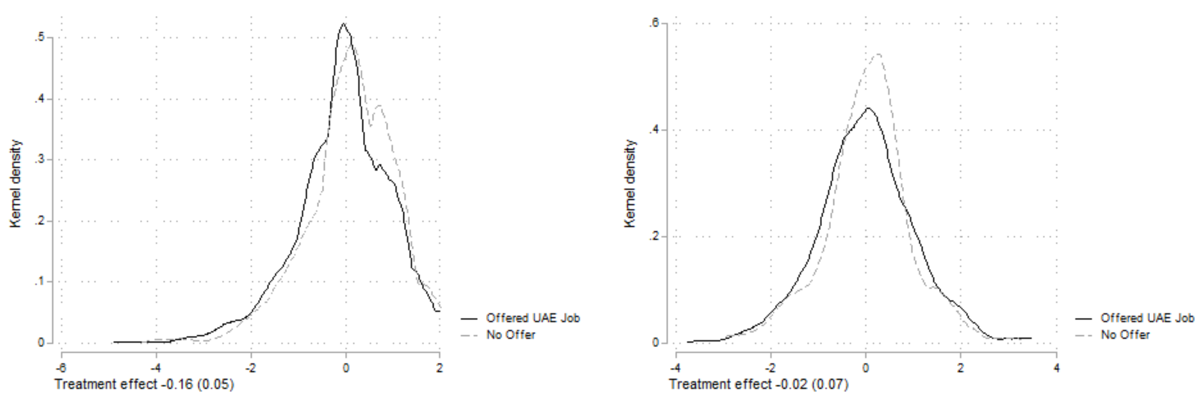


Notes: The figures show the distributions of the log difference between baseline expectations about earnings in the UAE and actual earnings in at follow-up using kernel density functions. Each variable is shown separately for individuals in the UAE and in India at follow-up.

Figure 5: Distribution of Well-Being and Work Satisfaction by Treatment Status

(a) Well-being

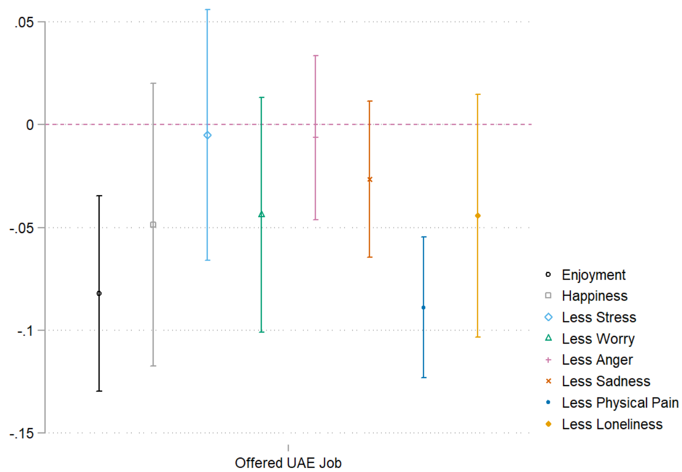
(b) Work Satisfaction



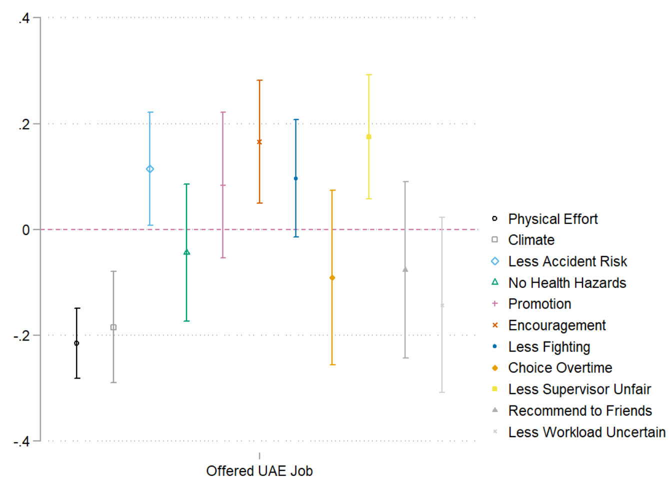
Notes: The figures show the distributions of the variables using kernel density functions. Each variable is shown separately for the treatment group and the control group.

Figure 6: Effects on Components of Well-Being and Work Satisfaction

(a) Well-being Components

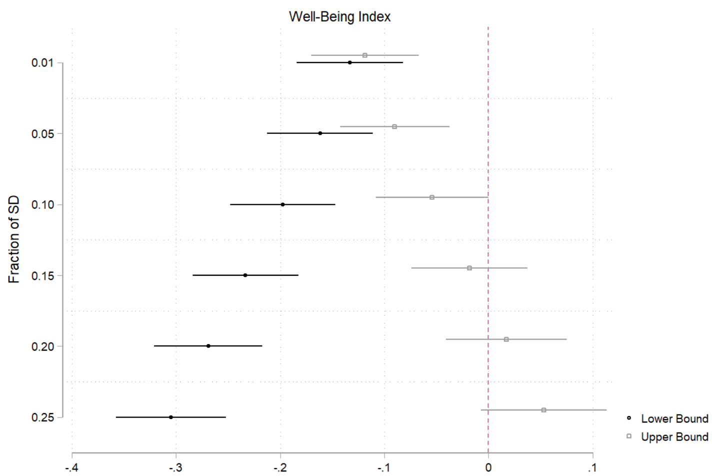


(b) Work Satisfaction Components



Notes: Each dot is the coefficient on being offered a UAE job in a regression with a separate outcome. The bands around the dot give the 90% confidence intervals. The regressions include randomization group fixed effects. In Panel A, the outcomes are the components that comprise the well-being index while in Panel B, the outcomes are the components that comprise the work satisfaction index.

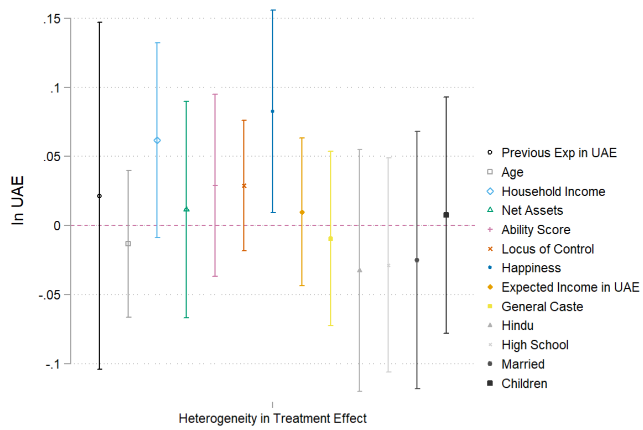
Figure 7: Varying the Levels on the Bounds on Well-Being Index Estimates



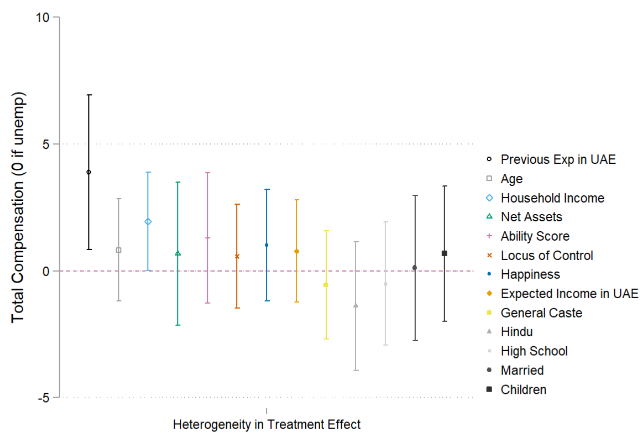
Notes: For the lower-bound estimates, each dot in black is the coefficient estimate where we assume that attritors have an outcome that is a fraction of a standard deviation below the mean where the fraction is given by the y-axis value. For the upper-bound estimates, each circle in gray is the coefficient estimate where we assume that attritors have an outcome that is that fraction of a standard deviation above the mean. The bands around a dot give the 90% confidence intervals.

Figure 8: Heterogeneity in Estimates

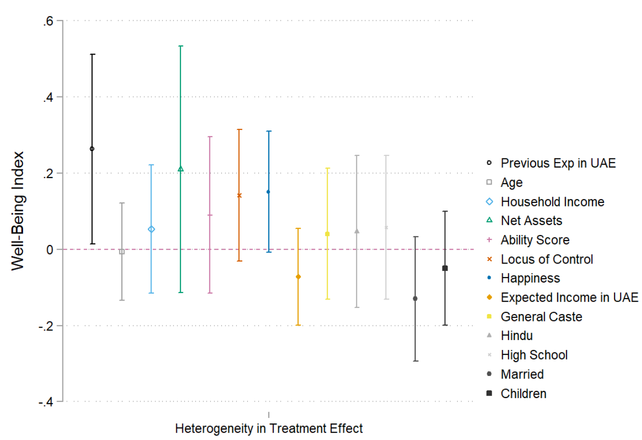
(a) In UAE



(b) Total Compensation



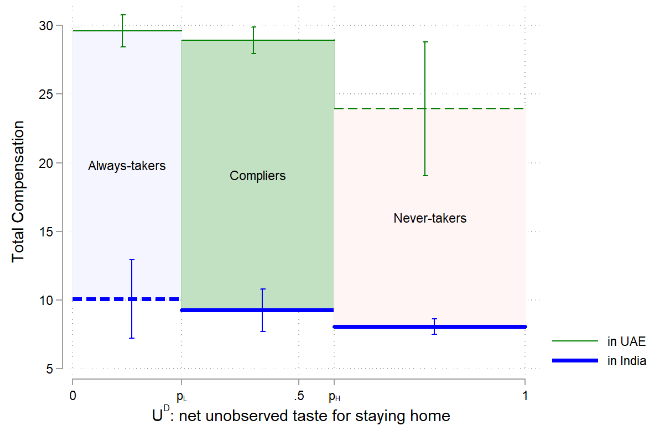
(c) Well-Being



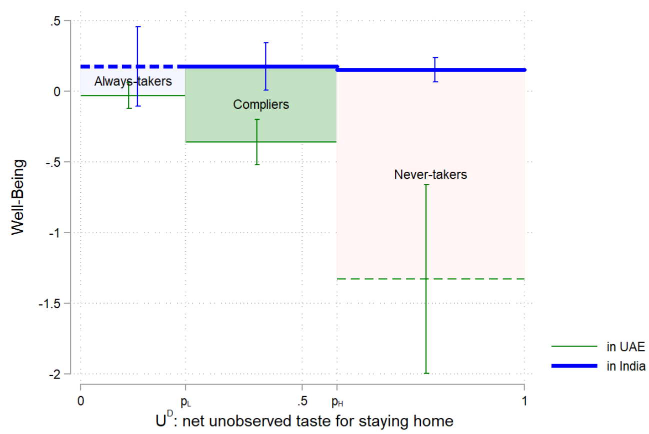
Notes: Each panel refers to a different outcome of interest. Each dot comes from a separate regression and gives the coefficient estimate for the interaction between that indicator variable (for whether the person is above median value) and the intention-to-treat variable. The bands around a dot give the 90% confidence intervals.

Figure 9: Average Outcomes for Always takers, Compliers and Never takers

(a) Total Compensation



(b) Well-Being



Notes: The bands around a line segment give the 90% confidence intervals for the group as compared to the compliers in the same country. Outcomes shown controlling for randomization group fixed effects, averaged over randomization groups.

7 Tables

Table 1: Summary Statistics on Labor Agents

	Mean	SD	N
Panel A: Agent Services			
Agent Use	1.00	0.00	1,223
Arranging for Travel	0.79	0.41	1,222
Paying for Travel	0.31	0.46	1,222
Helping with Logistics	0.85	0.35	1,219
Skills Training and Interview Prep	0.75	0.44	1,221
Applying for Passports	0.11	0.31	1,222
Applying for Visas	0.98	0.14	1,218
Paying for Visa Fees	0.38	0.48	1,129
Paying for Passport Fees	0.03	0.17	1,215
Access to Job Interviews	0.81	0.39	1,209
Help with Medical Screening	0.63	0.48	1,222
Panel B: Agent Fees			
Total Agent Fee	64,442.42	12,815.57	1,220
Agent Fee Paid Upfront	1,615.26	6,308.77	1,219
Agent Fee Paid Contingent	60,442.04	17,158.19	1,219

Notes: The data are from the follow-up survey and the sample includes only individuals in the UAE.

Table 2: Baseline Summary Statistics: Sample Applicants versus Population Statistics

	IHDS			Survey			
	Mean	SD	N	Mean	SD	N	p-value
Age	34.27	14.56	36443	28.14	6.22	4243	0.00***
High School and higher	0.37	0.48	36392	0.37	0.48	4242	0.65
Hindu	0.77	0.42	36443	0.77	0.42	4243	0.55
Muslim	0.16	0.37	36443	0.13	0.33	4243	0.00***
General Caste	0.33	0.47	36320	0.20	0.40	4215	0.00***
Scheduled Caste	0.25	0.43	36320	0.37	0.48	4215	0.00***
Other Backward Caste	0.36	0.48	36320	0.42	0.49	4215	0.00***
Scheduled tribe	0.05	0.23	36320	0.01	0.11	4215	0.00***
Annual earnings (in 1000's)	210.21	375.96	36443	154.41	117.93	4141	0.00***

Notes: The first three columns show summary statistics (mean, standard deviation and number of observations) from the IHSD 2011-2012 for men in our age range and in our states of analysis. The next three columns show summary statistics from our baseline survey of all job applicants (including workers who fail the job interview). The last column shows the p-value testing the difference between the means.

Table 3: Baseline Summary Statistics: Applicants Who Pass versus Fail the Screening

	Passed Workers		Failed Workers		Total	
	Mean	SD	Mean	SD	N	p-value
Age	28.00	6.13	28.76	6.63	4243	0.00
High School and higher	0.38	0.49	0.30	0.46	4242	0.00
Hindu	0.76	0.43	0.82	0.39	4243	0.00
Muslim	0.13	0.33	0.12	0.32	4243	0.54
General Caste	0.21	0.41	0.13	0.34	4215	0.00
Scheduled Caste	0.37	0.48	0.38	0.49	4215	0.50
Other Backward Caste	0.40	0.49	0.48	0.50	4215	0.00
Annual Household Income	154.56	117.26	153.71	121.26	4141	0.86
Expected Annual Income UAE	306.91	264.12	300.35	272.70	4216	0.55
Net Assets	899.55	1453.30	850.86	1327.27	2241	0.55
Ability Score	2.31	1.51	1.82	1.39	3680	0.00
Happiness	5.11	2.10	5.05	1.91	4244	0.46
Locus of Control	0.87	0.76	0.97	0.76	4123	0.00

Notes: Passed workers are screened by the firm as above the bar; this sample comprises of our treatment and control groups. Failed workers do not pass the firm's screening for a job offer. Annual household earnings, expected annual earnings in the UAE and assets are in thousands of rupees. The last column shows the p-value testing the difference between the means.

Table 4: Impact of Job Offer on Migration Outcomes

	Unweighted Rand Group FE	Weighted All Fe	N	Control Mean	Control Std.Dev.
In UAE	0.29***	0.24***	2,314	0.23	0.42
	(0.04)	(0.04)			
In UAE (Expanded)	0.23***	0.16***	3,557	0.25	0.43
	(0.03)	(0.02)			
Months in UAE	3.44***	3.28***	2,368	4.60	7.86
	(0.94)	(0.71)			
Home District Resident	-0.20***	-0.15***	2,314	0.57	0.50
	(0.05)	(0.04)			
Construction Job	0.14***	0.13***	2,008	0.71	0.45
	(0.03)	(0.03)			

Notes: Each row represents a different outcome variable and each column corresponds to different specifications. The first column includes only randomization group fixed effects. The second column adds fixed effects for enumerator as well as re-weights for attrition. Each coefficient estimate of the impact of a job offer is from a separate regression, and standard errors clustered by randomization group are shown in parentheses. The expanded version includes individuals for whom we do not have a follow-up survey but we have information from other sources (friends and family survey or MOL).

Table 5: Impact of Job Offer on Labor Market and Well-Being Outcomes

	Unweighted Rand Group FE	Weighted All FE	N	Control Mean	Control Std.Dev
Panel A: Labor Market					
Total Compensation	5.17***	4.48***	2,000	17.31	10.71
	(0.89)	(0.79)			
Total Compensation (0 if unemp)	5.81***	4.59***	2,365	13.56	11.87
	(1.00)	(0.90)			
Monthly Earnings	3.02***	2.76***	2,000	14.44	7.03
	(0.55)	(0.49)			
Monthly Earnings (0 if unemp)	3.68***	2.93***	2,365	11.31	8.61
	(0.67)	(0.62)			
Unemployed	-0.07**	-0.04	2,379	0.21	0.41
	(0.02)	(0.02)			
Work Hours	4.05***	2.91***	2,009	54.21	13.85
	(0.92)	(0.60)			
Want More Hours	-0.01	-0.01	2,008	0.63	0.48
	(0.04)	(0.03)			
Commute Time	-1.23	-1.00	2,005	35.33	38.78
	(2.33)	(1.79)			
Panel B: Imputed Values					
Total Compensation (0 if unemp)	4.84***	5.60***	2,603	16.00	12.57
	(0.86)	(1.36)			
Monthly Earnings (0 if unemp)	3.12***	3.93***	2,603	12.92	8.98
	(0.63)	(1.22)			
Panel C: Well-Being					
Well-Being Index	-0.16***	-0.13***	2,379	0.12	0.97
	(0.05)	(0.05)			
Work Satisfaction Index	-0.02	-0.04	2,006	0.03	0.93
	(0.07)	(0.07)			

Notes: Each row represents a different outcome variable and each column corresponds to different specifications. The units for earnings and compensation are in 1000's of INR per month. The first column includes only randomization group fixed effects. The second column adds fixed effects for enumerator as well as re-weights for attrition. Each coefficient estimate of the impact of a job offer is from a separate regression, and standard errors clustered by randomization group are shown in parentheses. Panel B imputes values of total compensation and average earnings using information from administrative data in cases where we lack follow-up survey data.

Table 6: Bounded Estimates of the Impact of Job Offer

	Lower Bound	Upper Bound	N
Panel A: Labor Market			
Total Compensation	2.39***	5.36***	3,169
	(0.70)	(0.64)	
Total Compensation (0 if unemp)	2.86***	5.78***	3,534
	(0.85)	(0.76)	
Monthly Earnings	1.13**	3.32***	3,169
	(0.42)	(0.35)	
Monthly Earnings (0 if unemp)	1.53**	3.83***	3,534
	(0.57)	(0.48)	
Unemployed	-0.10***	0.02	3,548
	(0.02)	(0.02)	
Work Hours	0.54	5.91***	3,178
	(0.60)	(0.50)	
Want More Hours	-0.10***	0.10***	3,177
	(0.02)	(0.02)	
Commute Time	-8.28***	5.27***	3,174
	(1.41)	(1.33)	
Panel B: Imputed Values			
Total Compensation (0 if unemp)	3.18***	5.61***	3,535
	(0.80)	(0.72)	
Monthly Earnings (0 if unemp)	1.75***	3.84***	3,535
	(0.53)	(0.48)	
Panel C: Well-Being			
Well-Being Index	-0.30***	0.05	3,548
	(0.03)	(0.04)	
Work Satisfaction Index	-0.23***	0.17***	3,175
	(0.04)	(0.04)	

Notes: Each row represents a different outcome variable and each column corresponds to different specifications. The first column assumes that attritors are 25% of standard deviation below their location-specific mean in the control group and 25% of a standard deviation above in the treatment group. The second column assumes that attritors are 25% of a standard deviation above their mean in the control group and 25% of a standard deviation below in the treatment group. Each coefficient estimate of the impact of a job offer is from a separate regression, and standard errors clustered by randomization group are shown in parentheses. The regressions include fixed effects for randomization group.

Table 7: Impact of Job Offer on Financial Outcomes

	Unweighted Rand Group FE	Weighted All Fe	N	Control Mean	Control Std.Dev.
Net Assets	-74.30	-79.48	2,316	943.75	1,383.85
	(78.22)	(78.06)			
Debt	6.39*	5.10	2,322	33.17	75.43
	(3.25)	(3.68)			
Remittances Last Month	4.02***	4.03***	2,356	7.64	20.26
	(1.42)	(1.38)			
Agent Fee Paid	14.37***	12.45***	2,303	28.73	32.04
	(2.42)	(2.28)			

Notes: Each row represents a different outcome variable and each column corresponds to different specifications. The first column includes only randomization group fixed effects. The second column adds fixed effects for enumerator as well as re-weights for attrition. Each coefficient estimate of the impact of a job offer is from a separate regression, and standard errors clustered by randomization group are shown in parentheses.

Table 8: Impact of Job Offer on Attitudes and Social Networks

	Unweighted Rand Group FE	Weighted All FE	N	Control Mean	Control Std.Dev
Panel A: Attitudes					
Rewards in India	0.11***	0.03	2,373	0.48	0.50
	(0.03)	(0.02)			
Rewards in UAE	0.03	-0.03	2,204	0.68	0.47
	(0.02)	(0.02)			
Income Gap in India	-0.01	-0.06***	2,367	0.75	0.43
	(0.03)	(0.02)			
Income Gap in UAE	0.11***	0.04	2,199	0.46	0.50
	(0.04)	(0.03)			
Rating Other Religion	2.73	3.28**	2,314	72.52	31.48
	(1.74)	(1.59)			
Rating Emiratis	2.77*	1.77	2,372	73.27	28.94
	(1.46)	(1.58)			
Importance Democracy	0.12	0.11	2,379	8.81	1.84
	(0.10)	(0.09)			
Panel B: Friends					
Closest Friend: Same Religion	-0.03*	-0.02	2,266	0.85	0.36
	(0.01)	(0.01)			
Closest Friend: Same Caste	-0.07***	-0.06**	2,309	0.67	0.47
	(0.02)	(0.02)			
All Friends: Same Language	0.03*	-0.02	2,364	0.75	0.43
	(0.02)	(0.02)			
All Friends: Same Religion	-0.03*	-0.01	2,363	0.38	0.48
	(0.02)	(0.03)			
All Friends: Same Caste	-0.01	0.01	2,355	0.24	0.43
	(0.02)	(0.02)			
Friends Similarity Index	-0.08*	-0.09**	2,366	0.06	1.01
	(0.04)	(0.04)			
Panel C: Work Team					
Team Size	-0.34	-0.06	1,972	8.58	10.06
	(0.59)	(0.57)			
Share Same Language	-0.03**	-0.03**	1,889	0.93	0.21
	(0.01)	(0.01)			
Share Same Religion	-0.01	-0.01	1,687	0.71	0.34
	(0.02)	(0.02)			
Team Similarity Index	-0.10**	-0.12**	1,897	0.09	0.93
	(0.05)	(0.05)			

Notes: Each row represents a different outcome variable and each column corresponds to different specifications. The first column includes only randomization group fixed effects. The second column adds fixed effects for enumerator as well as re-weights for attrition. Each coefficient estimate of the impact of a job offer is from a separate regression, and standard errors clustered by randomization group are shown in parentheses.

Table A.1: Baseline Summary Statistics: Attriters versus Non-Attriters

	Has Follow-up Mean	SD	No Follow-up Mean	SD	Total N	p-value
Age	27.90	6.30	28.20	5.78	3507	0.16
High School and higher	0.41	0.49	0.33	0.47	3507	0.00
Hindu	0.75	0.43	0.77	0.42	3507	0.15
Muslim	0.13	0.33	0.13	0.34	3507	0.70
General Caste	0.23	0.42	0.19	0.39	3481	0.00
Scheduled Caste	0.37	0.48	0.36	0.48	3481	0.39
Other Backward Caste	0.38	0.49	0.44	0.50	3481	0.00
Annual Household Income	155.12	116.96	153.48	117.88	3438	0.70
Expected Annual Income UAE	305.66	259.68	309.37	272.66	3479	0.70
Net Assets	881.62	1498.14	929.28	1376.24	1927	0.48
Ability Score	2.25	1.52	2.42	1.48	2943	0.00
Happiness	5.10	2.13	5.12	2.04	3507	0.86
Locus of Control	0.87	0.76	0.87	0.75	3423	0.88

Notes: The last column shows the p-value testing the difference between the means.

Figure A.1: Experiment Timeline

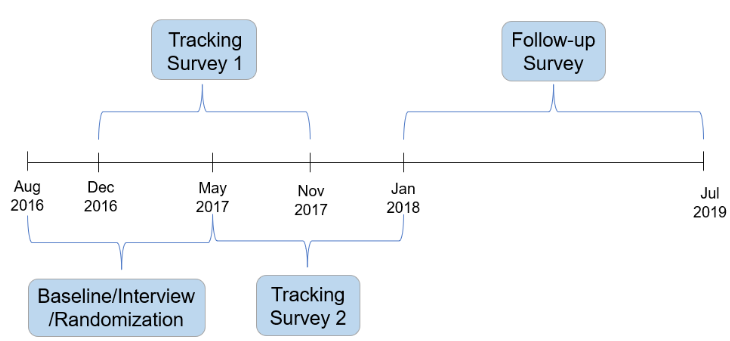


Figure A.2: Worker Home Districts

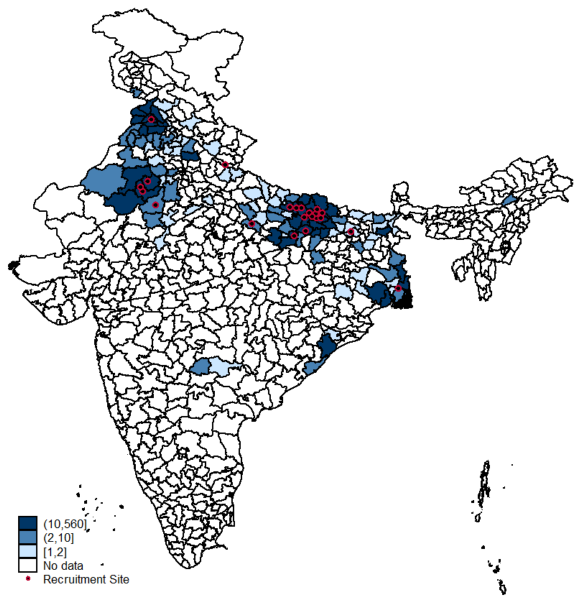


Figure A.3: Follow-Up Destinations of the Treatment and Control Groups

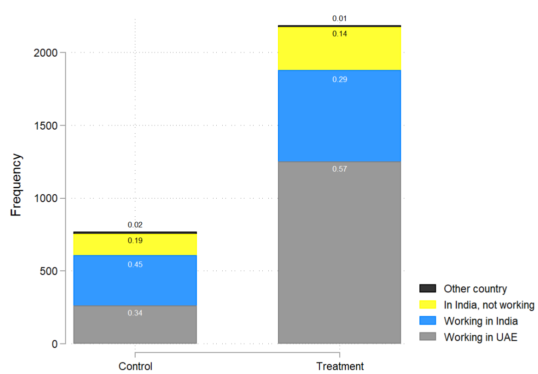
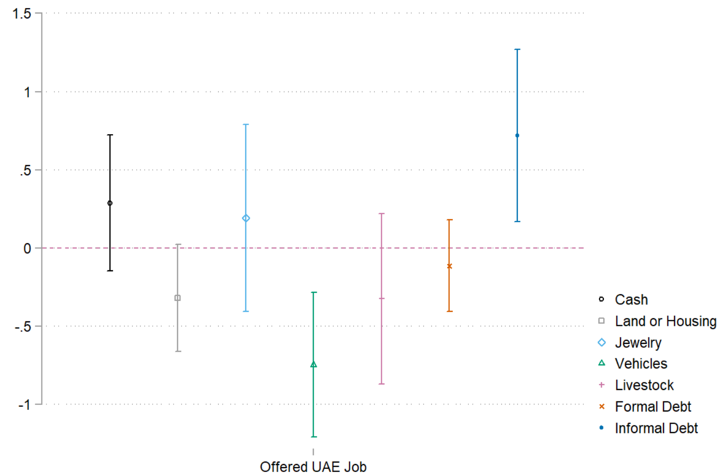
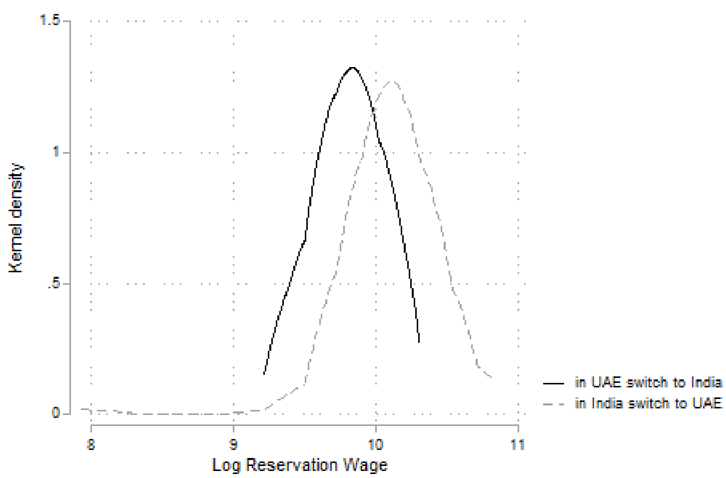


Figure A.4: Effects on Components of Assets and Debt



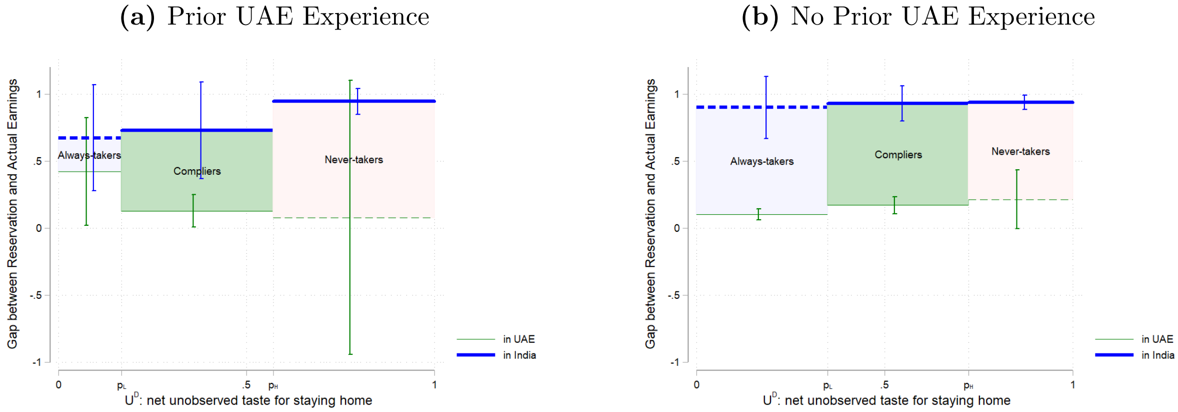
Notes: Each dot is the coefficient on being offered a UAE job in a regression with a separate outcome. The units for land or housing are in 10,000 rupees while the units for the other outcomes are in 1000 rupees. The bands around the dot give the 95% confidence intervals. The regressions include randomization group fixed effects

Figure A.5: Distribution of Country-Specific Reservation Wages



Notes: The figures show the distributions of the variables using kernel density functions. The logarithm of the reservation wage is shown separately for those in the UAE at the time of the follow-up survey (about their reservation wage for moving to India) and those in India (about their reservation wage for moving to the UAE).

Figure A.6: Gap between Reservation and Actual Wages by Prior Experience in UAE



Notes: The bands around a line segment give the 90% confidence intervals for the group as compared to the compliers in the same country. Outcomes shown controlling for randomization group fixed effects, averaged over randomization groups.

Table A.2: Baseline Summary Statistics by Treatment and Control Individuals

	Treatment		Control		Total	Uncond.	Condit.
	Mean	SD	Mean	SD	N	p-value	p-value
Age	27.99	6.15	28.04	6.06	3,507	0.80	0.91
High School and higher	0.38	0.49	0.39	0.49	3,507	0.61	0.70
Hindu	0.76	0.43	0.76	0.43	3,507	0.91	0.79
Muslim	0.13	0.33	0.13	0.34	3,507	0.77	0.79
General Caste	0.21	0.41	0.22	0.42	3,481	0.33	0.23
Scheduled Caste	0.37	0.48	0.36	0.48	3,481	0.88	0.99
Other Backward Caste	0.41	0.49	0.39	0.49	3,481	0.31	0.36
Annual Household Income	154.74	113.58	154.11	125.99	3,438	0.89	0.99
Expected Annual Income UAE	311.66	273.34	295.21	239.55	3,479	0.08	0.15
Net Assets	937.75	1,512.16	807.23	1,296.73	1,927	0.06	0.03
Happiness	2.32	1.51	2.28	1.49	2,943	0.49	0.49
Locus of Control	5.11	2.10	5.10	2.12	3,507	0.85	0.84
Ability Score	0.87	0.76	0.88	0.76	3,423	0.84	0.82

Notes: Annual household earnings, expected annual earnings in the UAE and assets are in thousands of rupees. The last two columns show the p-value testing the difference between the means. The first p-value is unconditional while the last column is conditional on the randomization groups.

Table A.3: Predicting Who Does Not Attrite Using Baseline Data

	Has Follow-up	
Number Contacts	0.19***	(0.05)
Number Mobile Numbers	0.03	(0.10)
Happiness	-0.05**	(0.02)
Ability Score	-0.06	(0.04)
Locus of Control	-0.02	(0.06)
Age	0.00	(0.01)
Log Household Income	-0.05	(0.07)
Log Expected Income UAE	0.02	(0.09)
Scheduled Caste	0.55*	(0.29)
Other Backward Caste	0.41	(0.28)
General Caste	0.53*	(0.30)
Other Caste	0.93**	(0.40)
Muslim	0.17	(0.17)
Sikh	-0.16	(0.25)
High School	0.06	(0.09)
More than High School	0.32**	(0.15)
Interview Language not Hindi	0.64*	(0.35)
Has Cell-Phone	-0.74	(0.50)
Observations	3355	
Pseudo R^2	0.127	

Notes: The coefficient estimates are from a logistic model where the outcome is whether the person has follow-up data (i.e. did not attrite from the survey). The regression includes controls for baseline enumerator, randomization group and home district. For missing observations in the continuous variables, we fill in the median observed value of the variable and include a separate indicator variable for whether the original value was missing. The standard errors clustered by randomization group are shown in parentheses.

Table A.4: Relationship between Contract Earnings and Survey Earnings

	Monthly Earnings (1)	Total Compensation (2)
Contract Salary	0.813***	0.896***
	(0.137)	(0.157)
Constant	8.358***	14.91***
	(2.202)	(2.536)
N	1134	1134

Notes: The estimates are run on individuals in our randomization sample for whom we have contract salary and compensation in the MOL data and earnings and compensation in the follow-up survey. Robust standard errors are shown in parentheses.

Table A.5: IV Estimates of Migration on Labor Market Outcomes and Well-Being

	Unweighted Rand Group FE	Weighted All FE	N	Control Mean	Control Std.Dev
Panel A: Labor Market					
Total Compensation	16.53***	16.62***	2,000	17.31	10.71
	(1.16)	(1.53)			
Total Compensation (0 if unemp)	19.45***	18.37***	2,365	13.56	11.87
	(1.31)	(1.62)			
Monthly Earnings	9.65***	10.22***	2,000	14.44	7.03
	(0.88)	(0.99)			
Monthly Earnings (0 if unemp)	12.31***	11.71***	2,365	11.31	8.61
	(1.06)	(1.25)			
Unemployed	-0.22***	-0.15*	2,379	0.21	0.41
	(0.07)	(0.08)			
Work Hours	12.75***	10.75***	2,009	54.21	13.85
	(1.68)	(1.86)			
Want More Hours	-0.02	-0.04	2,008	0.63	0.48
	(0.11)	(0.11)			
Commute Time	-3.89	-3.69	2,005	35.33	38.78
	(7.51)	(6.72)			
Panel B: Imputed Values					
Total Compensation (0 if unemp)	20.41***	24.37***	2,603	16.00	12.57
	(1.85)	(5.31)			
Monthly Earnings (0 if unemp)	13.15***	17.11***	2,603	12.92	8.98
	(1.71)	(5.06)			
Panel C: Well-Being					
Well-Being Index	-0.53***	-0.53**	2,379	0.12	0.97
	(0.18)	(0.21)			
Work Satisfaction Index	-0.07	-0.16	2,006	0.03	0.93
	(0.22)	(0.25)			

Notes: Each row represents a different outcome variable and each column corresponds to different specifications. The first column includes only randomization group fixed effects. The second column adds fixed effects for enumerator as well as re-weights for attrition. Each coefficient is the estimate of the impact of migration to the UAE (instrumented by the randomized job offer) on the outcome, and standard errors clustered by randomization group are shown in parentheses.

Table A.6: Baseline Characteristics for Always-takers, Compliers, Never-takers and Rejected Workers

	Compliers	Never-takers	Always-takers	Rejected	P-Value of Difference				
					C - R	NT - R	AT - R	C - NT	C - AT
Age	27.89	28.09	27.90	28.76	0.10	0.02	0.05	0.70	0.99
	(0.47)	(0.17)	(0.37)	(0.24)					
High School and higher	0.35	0.41	0.37	0.30	0.16	0.00	0.03	0.17	0.76
	(0.04)	(0.01)	(0.03)	(0.02)					
Hindu	0.74	0.77	0.75	0.82	0.03	0.00	0.02	0.47	0.84
	(0.03)	(0.01)	(0.03)	(0.01)					
Muslim	0.10	0.14	0.13	0.12	0.49	0.19	0.75	0.15	0.41
	(0.03)	(0.01)	(0.02)	(0.01)					
General Caste	0.20	0.22	0.22	0.13	0.05	0.00	0.00	0.73	0.61
	(0.03)	(0.01)	(0.03)	(0.01)					
Scheduled Caste	0.37	0.34	0.40	0.38	0.88	0.12	0.54	0.49	0.57
	(0.04)	(0.01)	(0.03)	(0.02)					
Other Backward Caste	0.40	0.42	0.36	0.48	0.06	0.00	0.00	0.71	0.37
	(0.04)	(0.01)	(0.03)	(0.02)					
Annual HH income	162.06	150.55	156.53	153.71	0.43	0.57	0.77	0.26	0.66
	(9.60)	(3.20)	(8.32)	(4.57)					
Expected Annual Income UAE	294.74	312.69	306.09	300.35	0.81	0.33	0.78	0.43	0.69
	(21.20)	(7.59)	(18.30)	(10.04)					
Net Assets	834.27	970.03	669.80	850.86	0.94	0.19	0.18	0.52	0.48
	(203.11)	(51.37)	(113.67)	(74.90)					
Happiness	5.62	4.90	5.10	5.05	0.00	0.09	0.75	0.00	0.01
	(0.16)	(0.05)	(0.13)	(0.07)					
Locus of Control	0.90	0.84	0.91	0.97	0.30	0.00	0.28	0.30	0.92
	(0.06)	(0.02)	(0.05)	(0.03)					
Ability Score	2.40	2.45	1.94	1.82	0.00	0.00	0.29	0.67	0.00
	(0.12)	(0.05)	(0.10)	(0.05)					
N	808	1878	895	748					

Notes: Annual earnings, expected earnings and assets are in thousands of rupees. Ability score ranges from 0-6, happiness score from 0-10 and locus of control from 0-2. Column 1-4 show the means with standard errors in parentheses. Standard errors were obtained from 500 bootstrap samples. Columns 5-9 show the p-values of the difference in means between compliers (C), never-takers (NT), always-takers (AT) and rejected workers (R).