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

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Abstract

We estimate the returns to temporary migration using a randomized experiment with Indian applicants for jobs in the UAE. Workers who migrate doubled their compensation. However, migrants paid substantial costs to labor intermediaries, and reported significant falls in well-being, driven by increases in physical pain, effort, and heat. The negative effects on well-being are consistent with the large share of workers offered jobs who did not migrate to the UAE. Estimating marginal treatment effect counterfactuals for workers who declined the offer, we find they would have similar pecuniary returns to migration, but experience even larger drops in well-being.

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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 those of 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.[1] 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 et al., 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, emphasizing the large earnings differentials and the fact that workers choose 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 on male workers in India. We partnered with the UAE Ministry of Labor (MOL) and two large, private construction firms.[2] 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, and 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 networks.

[1]The migrant flow between South Asia and the GCC countries is the second largest circular international migration corridor in the world after U.S.-Mexico (Azose and Raftery, 2019).

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

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.[3]

We find that the pecuniary returns to migrants from guest worker migration are large, consistent with evidence from previous work showing that households are better off. At the same time, however, the gains are a small fraction of the 10-fold GDP per capita differences between the UAE and India. While the pecuniary returns are attenuated by the costs paid to labor intermediaries, they are amplified when in-kind benefits 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 choose to stay in India. The presence of a large share of "never-takers" (who do not migrate regardless of whether they receive the randomized offer), despite large estimated pecuniary returns, suggests significant non-pecuniary costs from guest-worker migration.[4] Consistent with this interpretation, we find significant negative effects on subjective well-being, and some measures of job quality. In particular, we document that the jobs in the UAE are particularly unattractive relative to jobs in India in terms of the physical effort required in the job and the climate conditions. We find smaller and insignificant effects on negative emotions which might be expected to be lower for migrants, such as loneliness, stress, and anger. Consistent with their assessment of these particular job amenities, the well-being components that change significantly are higher physical pain and fewer experiences of enjoyment. The large share of never-takers suggests that a constraint on increased guest worker migration may lie in the choices of migrant workers themselves, and improvements in wages and working conditions in the UAE could increase take-up of guest worker offers.

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. Our data on expectations at baseline allows us to examine whether potential migrants have accurate information about their earnings prospects in the destination country. This is particularly important in this migration context where policymakers are concerned that workers are being deceived by unscrupulous labor intermediaries (UNODC,

[3]To our knowledge, the literature also lacks information on how the costs and benefits of migrant labor are distributed across workers, firms and labor intermediaries.

[4]The evidence we present on this is also consistent with Lagakos et al. (2023) whose structural model suggests that high disutility at the destination explains the lack of subsequent remigration among seasonal migrants within Bangladesh. We discuss widespread non-compliance in other IV-based papers that find high returns in Appendix 9.

2015). However, there has been little large-scale evidence comparing expectations and realizations for migrants of guest worker programs.[5]

Finally, we estimate marginal treatment effects (MTEs) of migration using the randomized offer as an instrument, and under a linear marginal treatment effect assumption (Brinch et al., 2017), impute potential outcomes for always-takers (who migrate regardless of whether they receive the randomized offer) and never-takers in the counterfactuals to their observed choices. While 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) which is widely used to study migration (Borjas, 1986). The MTE approach allows us to quantify the potential outcomes for those who choose not to migrate despite getting an offer, shedding light on the determinants of migration decisions. We find considerable heterogeneity in the marginal treatment effects: never-takers have somewhat lower UAE earnings, but significantly lower subjective well-being in the UAE than compliers or always-takers, suggesting that there is considerable heterogeneity in the taste (or other costs) for guest worker migration, even among workers who have selected into applying and are sufficiently skilled to pass the screening test. We then use our experimental estimates to bound the relative value of subjective well-being and income in the decision to migrate. Using prior estimates of the market power of UAE firms in recruitment (Naidu et al., 2016), we show that a doubling of total compensation (or similar improvements in the labor conditions of migrant workers would induce complete take-up of migration offers and increase efficiency.

The role of labor intermediaries for international migration in our context is also important.[6] For workers, labor intermediaries are essential for getting an international job. Among those who migrate to the UAE, 100% of our sample used a labor intermediary, paying on average 64,000 INR each.[7] 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.[8] One finding from our

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

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

[7]This corresponds to over USD 1000.

[8]While other recent papers have studied international labor market intermediaries (Bazzi et al., 2021; Fernando and Singh, 2021), they focus on exogenous variation in information about intermediaries (rather than exogenous variation in migration opportunities) and do not have data on the fees paid by migrants to the intermediaries, nor extensive data on prospective workers who choose not to migrate.

paper is that the bulk of intermediary fees are conditional on migration, and the earnings effects we find suggest that migrants could pay off any resulting debt relatively quickly. We can use our estimates to calculate that about 10% of the gains from international migration is captured by intermediaries. In this, we are related to a literature that has emerged on the role of intermediaries in trade and globalization.[9] As we detail below, agent fees in our context are 40% of annual household income in our sample, and are about five times higher, relative to the migration premium, than the Mexico-U.S. fees for intermediaries.[10] 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. These costs may be also correlated with unobserved characteristics of workers, making a randomized experiment important.

Our paper contributes to a literature estimating the impacts of international migration on migrant outcomes. The key issue in this literature is how to address selection in who migrates. Most of the existing literature on international migration uses natural experiments and other methods to solve the selection problem (see e.g. Grogger and Hanson (2011) and surveys by Clemens (2011); McKenzie and Yang (2022); Dustmann and Görlach (2016)). In terms of methodology, we are most similar to the literature that solves the selection problem with retrospective surveys of visa lottery participants. 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 $58k for Indian programmers in the 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 limited, despite long-standing

[9] Atkin and Donaldson (2015) show that in product markets intermediaries capture a significant share of the gains from trade liberalization. In agricultural markets, Bergquist and Dinerstein (2020), Dhingra and Tenreyro (2020), and Macchiavello and Morjaria (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).

[10] The migration premium is the additional amount workers would earn in the host country relative to what they would earn in their home country.

claims by economists that such programs are the most effective way to reduce global inequality (Milanovic, 2016; Weyl, 2018).[11] Using a retrospective survey of guest workers and a regression discontinuity in test scores, Clemens and Tiongson (2017) find migration from Philippines to Korea led to an increase in wages of over 200%.[12] Using a matching approach, Gibson and McKenzie (2014) estimate the impacts of a New Zealand seasonal worker program on Tongan and Vanuatu workers, finding a 35% increase in household per-capita income and significant and positive effects on household subjective well-being. Clemens (2018) studies the India-UAE migration corridor using a natural experiment of contracts cancelled during the financial crisis to look at household-level outcomes. Mobarak et al. (2023) finds a 60% return to household income five years after a visa lottery of Bangladesh-Malaysia guest worker migration.[13] We provide a comprehensive review of this literature in the context of our paper in Appendix 9.

We offer three key contributions to the prior literature. First, none of the prior literature on the returns to guest worker programs accounts for the costs of labor market intermediaries, or measure the contractual arrangements between brokers and workers. Second, unlike these other papers which focus on the outcomes for households well *after* the initial migration experience, our paper focuses on the contemporaneous outcomes of migrant workers themselves, providing an important complement to the existing research.[14] While the literature has generally focused on the financial benefits of temporary guest work accruing to households, our paper shows that these benefits come at the expense of non-pecuniary costs borne by the workers themselves. Thus, our survey of contemporaneous migration provides a fuller picture of the costs they bear while outside of the home country to provide benefits to their families. The focus in our paper on the migrant rather than the household allows us to be the first study on guest worker programs to document the worse work amenities and lowered subjective well-being of the workers themselves. These non-pecuniary determinants of migration

[11] For example, 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."

[12] Similar to our results, the deployment rate of successful test takers was only 71.2%, with more than a quarter of successful applicants not migrating to Korea despite these large returns. Details are in Appendix 9.

[13] Furthermore, while Bangladesh has a centralized lottery system, migration from India is decentralized and more similar to how most guest workers in different countries find jobs. Indeed, Mobarak et al. (2023) show large and significant differences in migration outcomes between households where migrants went via the lottery system versus through the decentralized process. Thus, their experimental variation does not isolate the effect of a guest worker job alone, but also the effect of eliminating the search frictions and intermediation fees through the centralized lottery.

[14] The one exception is Gaikwad et al. (2022) which focuses on political and social outcomes but does present the impact on earnings of migrants in a randomized experiment of job training and interview access for service jobs in the UAE. They do not look at well-being of the migrant, have a much smaller sample of 248 migrants from one state in India (Mizoram) and cannot disentangle the impacts of training from job placement.

decisions are important as they suggest policies that regulate conditions of work in host countries could expand migration. Third, we show that the MTE framework can be used to understand the migration decisions of potential guest workers and to demonstrate that there are efficiency losses associated with the market power of firms at destination. Taken together, our results suggest that existing GCC-style guest worker programs may not be achieving their full potential in terms of either efficiency or global redistribution.

We explore both physical and psychological dimensions of well-being. Individual migrants, separated from their primary social networks, may also bear large psychological costs. Reports of loneliness and alienation among international migrants are common (Ponizovsky and Ritsner, 2004). We are also able to look at other ways migration changes an individual, including their friendship networks. While migrants experience isolation from their pre-existing social networks, migration also potentially exposes workers to much more diverse people and the opportunity to form new social ties.

Other research on guest worker programs has focused on changing features of such programs on both wages and employer market power (Naidu et al., 2016), or information experiments, such as informing workers about mortality rates (Shrestha, 2019). Kosack (2020) 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 Alvaredo et al. (2019) describes 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 intermediary payments. We also examine other impacts including well-being, work satisfaction, financial outcomes, attitudes and social networks. In our second-to-last section, we look at heterogeneity in outcomes. This includes interpreting our data through a generalized Roy model of migration and extrapolating potential outcomes from compliers to always-takers and never-takers. Finally, we discuss our estimates in the context of the broader literature and use numbers from prior research to calculate the efficiency gains of increasing compensation for guest workers.

2 Background on the Migration Supply Chain

The recruitment of migrants to GCC countries is a decentralized process throughout India.[15] 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 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. Labor brokers 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.

The search process through which workers find out about job opportunities and travel to interview sites is facilitated by 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.[16] 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 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 in the UAE 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%

[15] See Naidu et al. (2016) for more details on the structure of the migrant labor market and the *kafala* system within the UAE. Briefly, workers are on fixed 2-year contracts with no opportunities to transition employers except at the end of the contract. If workers want to leave their jobs to return to India without the permission of their employer, they need to cover their airfare back home and may be fined and blacklisted from future employment opportunities in the UAE. Most labor contracts include room and board and some medical coverage. There is no legal minimum wage, and little to no native Emirati employment in the sectors that employ most migrants.

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

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.

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.[17]

3 Experimental Design and Data Collection

We partnered with two large construction firms in the UAE and the UAE Ministry of Labor. The construction sector in the UAE employs the largest number of migrant workers (25%). While earnings

[17]This includes our survey as well as Irudaya 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.

does not capture all of the important dimensions of jobs, Appendix Figure A.1 shows where the two construction firms in our analysis are relative to the distribution of job offers in the UAE (using administrative data from the MOL). Our two experimental firms were both almost identical to each other in terms of average offers and also extremely close to the modal salary both in the whole UAE distribution as well as in the construction sector.

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.[18] 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 from the UAE.[19] While firms may have a target number of positions to fill in a recruitment round, there is some uncertainty over 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.[20] In those cases, we conducted the baseline survey via phone within a couple of days of their interview.[21]

All of the positions were in construction work, including job titles such as carpenter, mason, painter, steel fixer and general helper. Within a job-firm combination, offered wages have very little variation, and there is no opportunity for bargaining after recruitment.[22] At the end of the day, the firm's interviewers provided us with a list of people who passed the firm's selection process. There were 3507 workers who passed the screening. 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. Our randomization process was a natural extension of an existing system in which firms request visas from the MOL and

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

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

[20]This occurred for 13% of our baseline surveys.

[21]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.

[22]Offered wages reflect the base salary so differences between earnings realizations and the offer can be driven by overtime and promotions. The lack of variation in offered wages within a job-firm combination implies that they do not change the offers based on local conditions such as the local wage rate.

sometimes are granted all of them and sometimes fewer than they request.[23] The job interviews and our accompanying baseline surveys happen between August 2016 and May 2017. Our enumerators surveyed the respondents at baseline, tracking and follow-up without the presence of any personnel of the UAE employers to insure unbiased responses.

The next stage of the process involved the usual medical screening, criminal record check and background screening of all visa applicants.[24] The vast majority of workers pass this.[25] The (few) workers who do not pass this background check 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 UAE arrive there to 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 construction jobs in the UAE different from the population of young men in India? Second, are the individuals who fail the job screening different along observables from the individuals who pass?

In order to assess selection into applications and interviews for these jobs, we compare baseline characteristics of the 4243 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 a similar amount of education with 37% of both samples having a high school degree. 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. Our sample is slightly but significantly less Muslim than the IHDS sample average. The average annual household income for our analysis group is about 25% lower than the population average. Overall, this suggests that there is negative selection into applying for these jobs.

Next, we compare baseline characteristics of the individuals who pass the screening test by the UAE firms with those who fail in Table 3.[26] The men searching for international jobs average around

[23] 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. There was no net decrease in the total number of workers recruited to the UAE as a result of this study.

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

[25] Based on a small sample from our second tracking survey, 5% of our treatment group did not pass the background screening, and another 2.7% failed the medical screening.

[26] Note the number of observations vary across variables because we were unable to administer the visually based Ravens-style ability

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 earnings are converted to 2017 rupees for comparability with the survey data. 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.

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 are more likely to be lower caste. They also score lower on a Ravens-style ability test and have higher locus of control. This suggests some positive selection into passing the migration screening skills test. However, this selection is not positive along all dimensions, as unsuccessful applicants 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 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:[27]

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

test for the phone baseline workers, and the question about assets was only added in 2017.

[27] 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.

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

	Passed Workers			Failed Workers			
	Mean	SD	N	Mean	SD	N	p-value
Age	28.00	6.13	3507	28.76	6.63	736	0.00***
High School and higher	0.38	0.49	3507	0.30	0.46	735	0.00***
Hindu	0.76	0.43	3507	0.82	0.39	736	0.00***
Muslim	0.13	0.33	3507	0.12	0.32	736	0.54
General Caste	0.21	0.41	3481	0.13	0.34	734	0.00***
Scheduled Caste	0.37	0.48	3481	0.38	0.49	734	0.50
Other Backward Caste	0.40	0.49	3481	0.48	0.50	734	0.00***
Annual Household Income	154.56	117.26	3438	153.71	121.26	703	0.86
Expected Annual Income UAE	306.91	264.12	3479	300.35	272.70	737	0.55
Net Assets	899.55	1453.30	1927	850.86	1327.27	314	0.55
Ability Score	2.31	1.51	2943	1.82	1.39	737	0.00***
Happiness	5.11	2.10	3507	5.05	1.91	737	0.46
Locus of Control	0.87	0.76	3423	0.97	0.76	700	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.

This equation includes fixed effects for the randomization group, which corresponds to each recruitment location and day for a particular construction firm.[28] This is necessary as the randomizations are done within these groups. In specifications with additional controls, we also include fixed effects for the enumerator, to account for differences in the way that each enumerator may ask the survey questions. Standard errors are clustered by randomization group.[29]

Appendix Table A.1 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 to take the job in the UAE, and control workers can get offers from other UAE firms, or even the same UAE firm later at a 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 58% of the treatment group is working in the UAE at the time

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

[29]We cluster because of unobserved intragroup correlation in the outcome within each randomization round. For example, if people who respond to a job advertisement in one month could have a common unobserved shock to outcomes from people who respond to a job advertisement three months later.

of the follow-up as compared with 26% 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 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.[30] We also conducted a phone survey of friends and family using contact information from the baseline to try to obtain updated contact information for the survey.[31] 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 and places to talk to the workers without firm representatives present.

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.[32] 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.

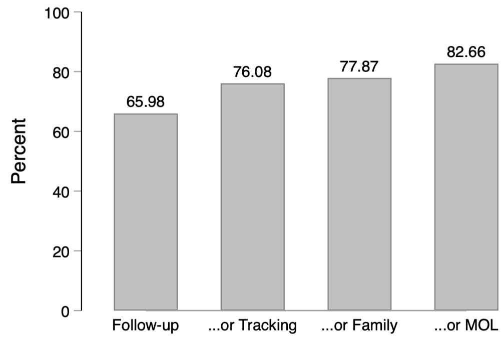
Overall, our attrition rates are similar to or smaller than other comparable studies, but are somewhat imbalanced. Clemens and Tiongson (2017) interview 44% of applicants migrating from Philippines to Korea. Mobarak et al. (2023) interview 68% of their control group and 69% and 94%

[30] The timeline for the survey data collection is shown in Appendix Figure A.4. The first phone tracking survey begins four months after we begin our baseline surveys, and the second tracking survey begins six months after that.

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

[32] This was matched into our sample using passport numbers to labor contracts in the UAE after the start of our experiment and before Fall 2017 (when we received the administrative data).

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.

of their two treatment groups. Gaikwad et al. (2022) find 63% of their sample in their endline survey. Similarly, we have more attrition in the control group than treatment group, and the attriters are different from non-attriters along baseline characteristics.[33]

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.

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

[33]See Appendix Table A.2.

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)			
Home District Resident	-0.20***	-0.15***	2,314	0.57	0.50
	(0.05)	(0.04)			
In UAE Experiment Firm (Expanded)	0.30***	0.22***	3,481	0.15	0.35
	(0.04)	(0.03)			
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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively. 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).

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 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 intent-to-treat results. The intent-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 have other data including the friends and family surveys and the administrative data from the MOL to determine whether they went to the UAE. The treatment effects remain positive and significant at the 1% level but the magnitudes here are slightly smaller.

In the third 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 as well as 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. The coefficient 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 on going to the UAE, suggesting that a large share of the control group are also migrating out of their home district but staying within India.

In the second-to-last row, we look at whether the person is working in the firm in the UAE for which they interviewed when they were randomized into the treatment and control group. Fifteen percent of the control group ends up at the same firm.[34] The treatment group is 30% more likely to be in the firm in the UAE for which they interviewed in the baseline survey in the parsimonious specification and 22% more likely with the additional controls and weighting. Both estimates are significant at the 1% level, and show that a job offer from a specific firm is an important determinant of the migration decision.

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 subjects' 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.[35] 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

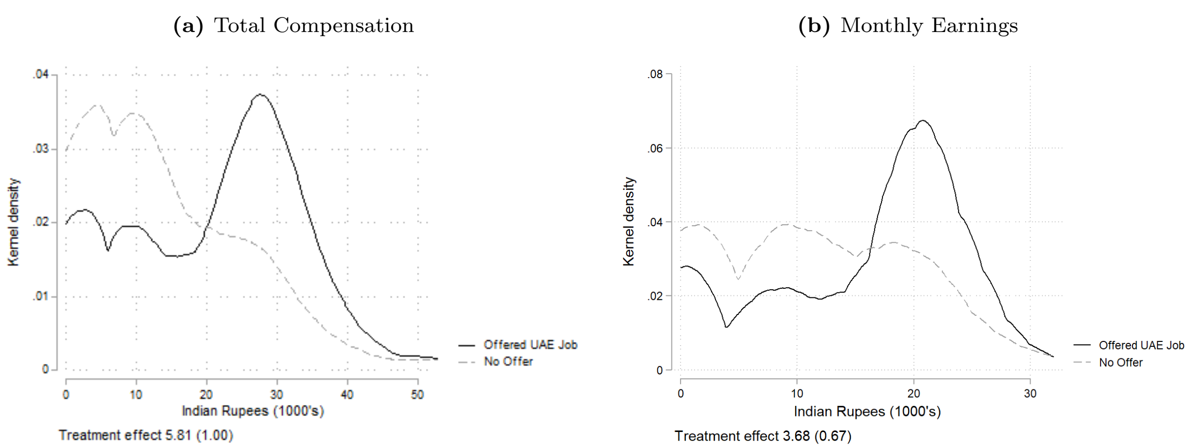
[34] This can occur either through the workers interviewing with the same firm again at a subsequent recruiting round or through unobserved noncompliance with the treatment assignment by the firms.

[35] Appendix Table A.4 shows the wording of the questions corresponding to the outcomes collected in the follow-up survey.

compensation per month in thousands of rupees.[36] The total monthly compensation of the treated individuals is 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.[37]

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.

Figure 2: Distribution of Earnings and Compensation by Treatment Status



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.

Getting the job offer in the UAE also decreases the probability that individuals in our sample 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.

[36] 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.

[37] 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.

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 per Week	4.05***	2.91***	2,009	54.21	13.85
	(0.92)	(0.60)			
Prefer Fewer Hours	0.01	0.00	2,008	0.04	0.19
	(0.01)	(0.01)			
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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively. Panel B imputes values of total compensation and average earnings using information from administrative data in cases where we lack follow-up survey data.

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 number of people in the sample are unemployed (and 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 2.9 to 4 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 fewer hours of work. Very few workers (4%) in the control group would prefer fewer hours.[38] There is no statistical difference for the treatment group on this preference despite the fact that the treatment group is working substantially more hours.[39] 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 well 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 and housing provided by the employer.

[38] On average in the control group, 63% would prefer more hours and the remaining 33% would prefer the same number of hours.

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

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 et al. (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 the survey data for individuals for whom we have both data.[40] 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.[41] 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 people have the right expectations regarding the returns to migration at the time that they are making their decision (McKenzie, 2023). Numerous stories abound documenting unscrupulous practices by labor intermediaries who promise jobs with higher salaries or better conditions and benefits than reality.[42] In this particular context, this can also arise not only 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 and how much they are actually earning at the time of the follow-up survey. Figure 3 shows the log difference between their actual earnings in the follow-up survey and the amount that they expected to earn prior to migration for those in the UAE at follow-up (in the solid black line) as compared to those in India at follow-up (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

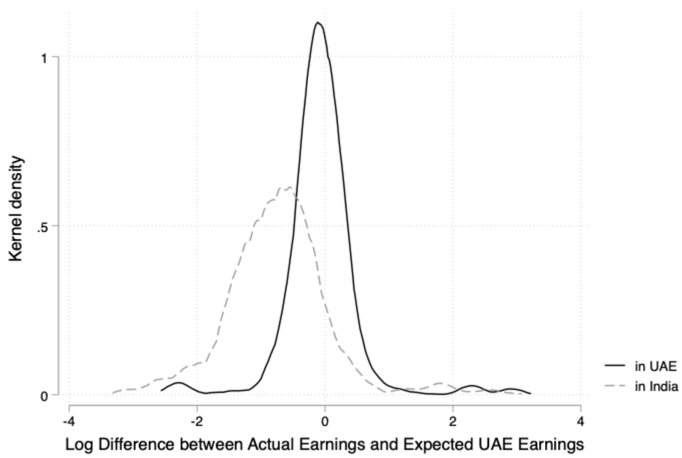
[40]The estimates are shown in Appendix Table A.6.

[41]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.

[42]For specific anecdotes, see for example Auwal (2010).

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.

Figure 3: Distribution of the Gap between Expected UAE Earnings and Actual Earnings by Current Country of Residence



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

For those in India at the time of follow-up, 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, an expected gain of 73% is not enough to induce them to migrate on average as their reservation earnings for migration require 87.8% higher earnings.[43]

In addition to earnings, we also asked in our baseline survey about their expected duration of stay in the UAE. The average expected duration in the UAE is 32 months. The initial contract length is 24 months, and 70% of workers report 24 months (exactly) as their expected duration, implying that they only plan to stay the minimum required length of the work contract. Thus, workers are not anticipating spending a long time in the UAE, despite the fact that they anticipate the wage

[43]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 that we describe in more detail below.

differentials to be quite large.

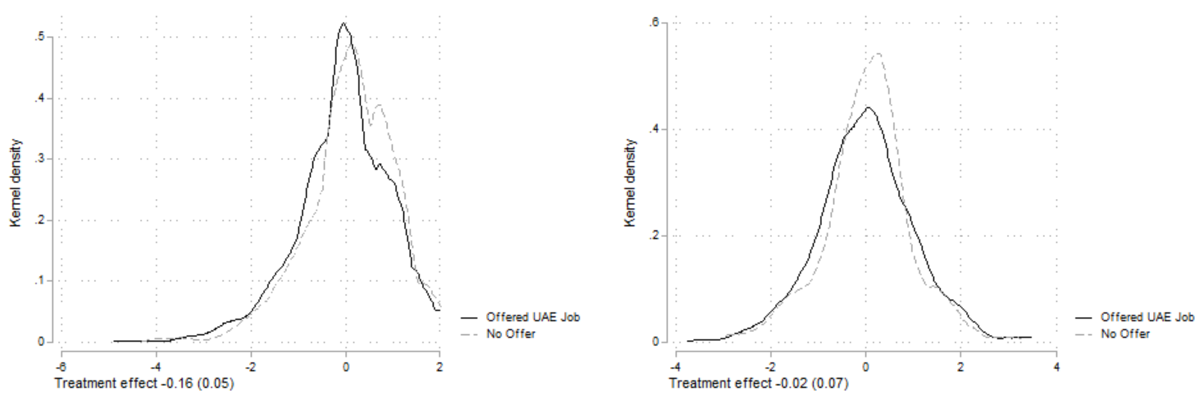
In Appendix 8, we present evidence on non-pecuniary costs of migration using reservation wages reported by migrants and non-migrants in their counterfactual location. Workers in the UAE report being willing to accept much lower wages to work in India, while workers in India report a much higher reservation wage for working in the UAE.

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 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.[44] First, Panel A of Figure 4 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 of 16% of a standard deviation for treated relative to control.

Figure 4: 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. Both outcomes are standardized to have overall mean zero and unit standard deviation.

[44]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.

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% of a standard deviation 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 5. The components are all standardized so that negative coefficient values correspond to 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).[45] 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 control group. Perhaps surprisingly, the impact of getting an international job offer on loneliness, while large in magnitude, is not statistically different from zero.

We also ask a set of standard questions 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.

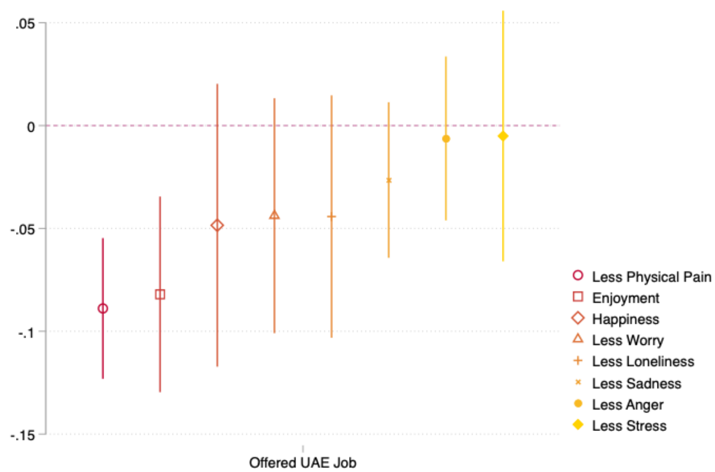
Panel B of Figure 4 shows the density functions for the index of work satisfaction for the treatment and control groups. The mean of the distributions are very similar though there is a bit more dispersion in the treatment group than in the control group. The coefficient estimates from the regressions (shown in the last row of Table 5) are not statistically different from zero. While media reports on migrants working in the Gulf focus on poor working conditions (e.g. McQue, 2022), our results indicate that *overall* working conditions in India are similarly bad.

The regression coefficients for each component of work satisfaction are shown in Panel B of Figure 5. 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 corresponds to them feeling more physical pain (Panel A of Figure 4).

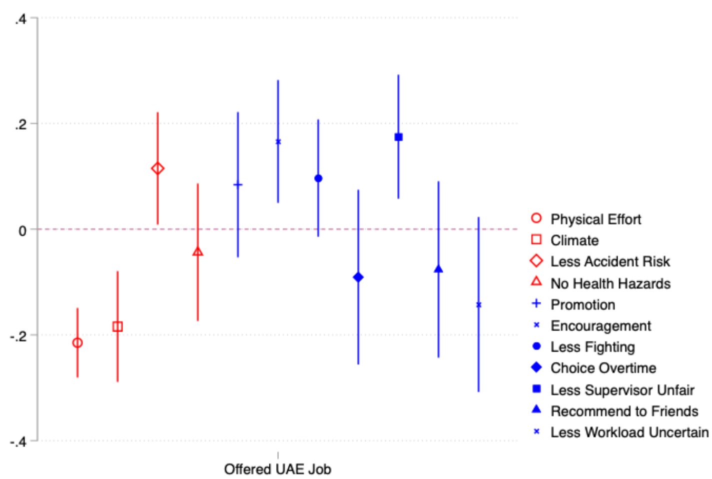
[45] These findings are similar to Blattman and Dercon (2018)'s study that find negative effects on physical health for those who randomly received a formal, industrial job offer in Ethiopia, although those offers did not come with significantly higher wages.

Figure 5: 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, with physical work conditions in red and others in blue. Each question is standardized to have overall mean zero and unit standard deviation.

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. The negative effects are concentrated in the physical dimensions of work. Workers 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 they are more likely to report loneliness (though the estimate on loneliness is not statistically significant).[46] The negative effects of migration in our sample have less to do with psychic experience of loneliness and distance from friends and family, and more to do with the physically taxing nature of the work. In contrast to Stillman et al. (2015), who find negative effects of permanent migration on affective happiness and respect but positive effects on mental health, we find little evidence of significant effects on emotional components of well-being, and much more on physical dimensions, such as pain, effort, and heat.

Our results on the disamenity of climate and heat exposure suggest that the optimal design of guest worker programs may be modified by climate change (Bank, 2021). Rising temperatures may worsen both amenities and productivity of construction jobs in destination countries like the UAE.[47] At the same time, rising temperatures may also worsen circumstances in poor countries, including India, and thus raise the demand for guest worker migration. While international migration is a key adaptation margin (Desmet and Rossi-Hansberg, 2015), designing guest worker programs to handle future climate change may have to account for the strength of these two forces.

While subjective well-being reflects a wide variety of work and non-work related conditions, there is evidence that higher income itself raises well-being: a meta-analysis by McGuire et al. (2022) finds that a 100% increase in income due to unconditional cash transfers in poor countries raises well-being by over 10% of a standard deviation. Using lottery winners, Lindqvist et al. (2020) find that the causal effect of a one point increase in log income is worth 0.38 on a standard deviation of overall life satisfaction, very similar to descriptive evidence from Stevenson and Wolfers (2013). The negative effect of migration on well-being is thus net of the (large) effects on income, and thus imply evern larger reductions in the non-pecuniary component of well-being.

[46] This finding is consistent with evidence presented below, where we show that migrants' friendship networks change, suggesting that they make new friends in the UAE, and these friends are somewhat less homophilic than the friendship networks in the control group.

[47] Iskander (2021) argues that GCC implementation of new climate-resilient construction technologies requires more "high-road" migrant construction labor relations for specialized training and retention.

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 impute 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 are calculated separately 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 6, we vary the assumptions about attritors being different fractions of a standard deviation above and below the mean rather than just the 25% fraction that are presented in Table 6. Reassuringly, the results on well-being are robust to a slightly lower fraction above the mean in Figure 6. The bounding estimates are robust if we assume that all attritors are 10% of a standard

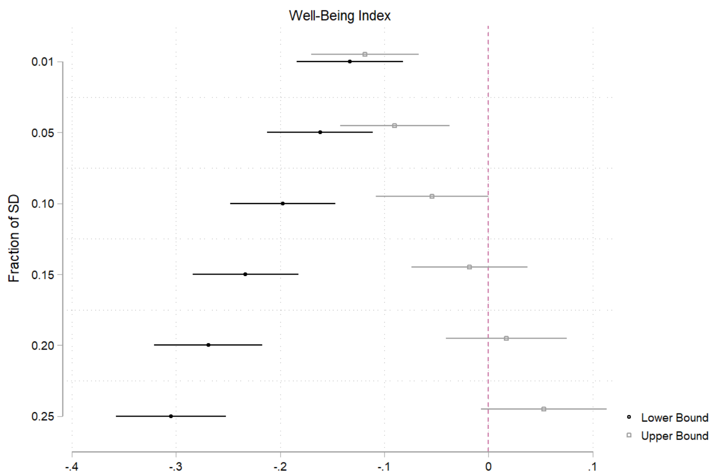
Table 6: Bounded Estimates of the Impact of Job Offer

	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 per Week	0.54	5.91***	3,178
	(0.60)	(0.50)	
Prefer 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 a standard deviation below in the treatment group and 25% of a standard deviation above their mean in the control group. The second column assumes that attritors are 25% of a standard deviation above in the treatment group and 25% of standard deviation below their location-specific mean in the control 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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively. The regressions include fixed effects for randomization group.

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.

Figure 6: 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.

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.[48] We look separately at whether the UAE job offer affects total debt in the second row. We 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 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

[48] Appendix Figure A.5 shows the estimates for each component of total assets. There is a significant decline in the value of vehicle and livestock assets for the treatment group relative to the control 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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively. All outcomes are in 1000's of INR.

average 4020 INR more per month than those who did not receive a UAE job offer in the parsimonious specification and 4030 INR more with additional controls.[49] 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 has 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.[50] 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.

[49] The impact of international migration on remittances is larger than the impact on monthly earnings, but smaller than the impact on total compensation, because a majority (57% in Table 4) of control group workers are living outside of their home districts with no in-kind compensation and must pay for room and board, increasing the gap in remittances.

[50] 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.

4.6 Impacts on Social Networks

As a component of migrants' well-being, we consider how the experience of international migration alters people's social networks. If workers' social networks adapt to their new context, this could explain the lack of significant impact on the loneliness component of well-being. In the first row of Table 8, we see that getting an international job offer corresponds to a decrease in the probability that the person's closest local friend has the same religion by 3 percentage points in the parsimonious specification.[51] This estimate is significant at the 10% level but loses significance with the additional controls and weights. Similarly, the probability that their closest friend is of the same caste fell. 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 addition to questions on their closest friends, we also ask a set of questions regarding whether they have any friends who speak a different language, is from a different religion or is from a different caste. The estimates on these measures are sensitive to the specification and not significantly different 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. Overall, this suggests that migrants are making new friends, who are more different from them.[52]

4.6.1 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. In Panel A of Figure 7, we look at the outcome of migrating to the UAE. This provides us with insight into whether the 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

[51] For those in the UAE, they are asked about their closest friend in the UAE. For those in India, they are asked about their closest friend in India.

[52] Appendix Section 7 looks at the impacts of the getting a job offer in the UAE on co-worker networks and whether the exposure to new people and experiences in a new country alter attitudes and perceptions about other groups of people.

Table 8: Impact of Job Offer on Social Networks

	Unweighted Rand Group FE	Weighted All Fe	N	Control Mean	Control Std.Dev.
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)			

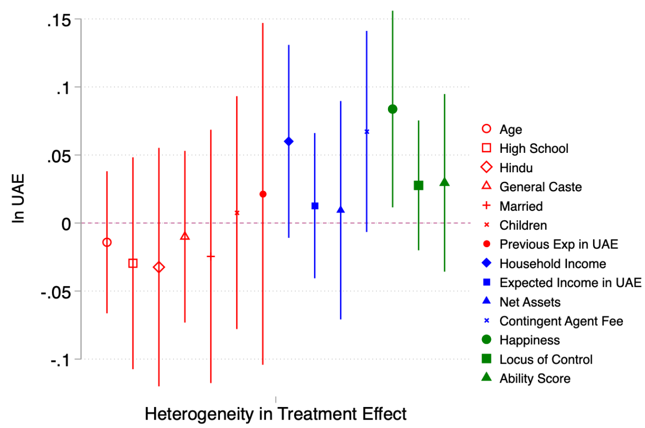
Notes: Each row represents a different outcome variable and each column corresponds to different specifications. The first column includes only randomization group fixed effects. The second column adds fixed effects for enumerator as well as re-weights for attrition. Each coefficient estimate of the impact of a job offer is from a separate regression, and standard errors clustered by randomization group are shown in parentheses. ***, **, * denotes significance at the 1, 5 and 10% levels respectively.

of the interaction between the indicator and treatment. For most variables, there is no significant heterogeneity 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.

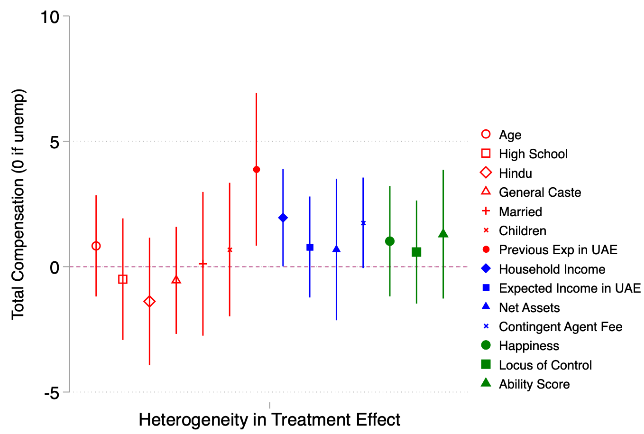
Next, we look at heterogeneity in these estimates when the outcome is total compensation in Panel B of Figure 7. Again, most of the estimates are not significantly different from zero at the standard levels. Those with prior work experience in the UAE earn substantially and significantly more when offered 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: none of the variables that predict passing the skills test predict higher earnings in the UAE.

Figure 7: Heterogeneity in Estimates

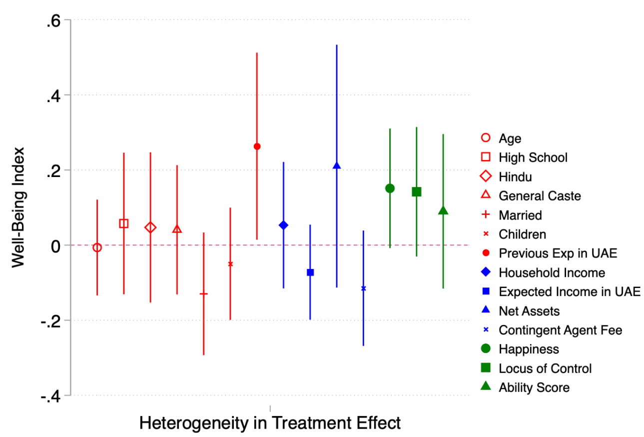
(a) In UAE



(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. The interactions are grouped by demographics (in red), financial variables (in blue), and psychometric measures and ability (in green).

Finally, in Panel C of Figure 7, 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 to the pool of potential recruits.

But this pattern of heterogeneity by previous experience is also consistent with the presence of non-pecuniary disamenities from UAE migration: workers with previous experience have higher wages and higher well-being from migration, but also are no more likely to migrate, suggesting there are relatively better non-pecuniary amenities (that do not raise well-being) in their options in India. In particular, it suggests the disamenities of guest worker migration are not due to uncertainty about conditions in the UAE, as presumably these are attenuated among migrants with previous UAE experience and yet there is no difference in the probability of accepting the offer. The pattern of heterogeneity by agent fee is suggestive: workers who have to pay more to their agents are more likely to take-up jobs (significant only at the 13% level) and get higher compensation (significant only at the 11% level). This suggests that agents may be playing an important role in arbitraging the migrant labor market, as workers are willing to pay to get better paying jobs.

It is noteworthy that there are no significant differences in any of these three key outcomes by either marital status or having children.[53] While it is likely that the migration decisions of these workers and the substantial remittances they send home improve the welfare of household members at home in India, being married and having children does not change the propensity of those given an offer to migrate, their earnings or their well-being.

4.6.2 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 et al., 2017; Kowalski, 2021; Heckman and Vytlacil, 2007a,b). We are interested in knowing whether the workers who do not take the offer when given are doing so because of lower pecuniary returns or other, non-pecuniary costs or tastes for staying in India. The empirical model has potential workers with utility for staying home (or distaste for migrating), denoted U^D. A high

[53] 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.

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, but could also be a reduced form representation including various types of search frictions or other obstacles 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. An individual i migrates ($D_i = 1$) if the benefits minus costs, including the unobserved disamenity of migrating, are greater than 0:

$$D_i = 1 \iff \gamma Z_i - U_i^D > 0 \tag{2}$$

The first-stage regression of D on Z recovers an estimate of γ. The randomization assumption guarantees that $Z \perp Y^{UAE}$, Y^{India}, U^D, but allows arbitrary correlations between Y^{UAE}, Y^{India}, and U^D. This allows, for example, individuals who have a high utility U_i^D for staying in India to have either higher or lower returns to migrating, $Y_i^{UAE} - Y_i^{India}$, than individuals with a low U_i^D.

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 suppress any dependence on observable Xs. We have then an expression for the marginal treatment effect as a function of the unobserved disamenity from migration given by:

$$MTE(u) = E[Y^{UAE} - Y^{India} | U^D = u]. \tag{3}$$

The MTE in total compensation is the pecuniary return to migrating to the UAE. If all pecuniary costs and benefits are observed, then the MTE in compensation 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), by extrapolating potential outcomes for always-takers and never-takers. Note that monotonicity means that never-takers (who will not migrate regardless of whether they receive the randomized offers) must have higher U^D than treated compliers (who got offers and migrated), and always-takers (who migrate regardless of receiving the randomized offer) must have lower U^D than untreated compliers (who did not get an offer and stayed in India). If the MTE is linear, then the potential outcomes are linear, and monotonicity is sufficient to recover potential outcomes for non-compliers.

In Figure 8, 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. Under the Roy model interpretation, the farthest right group, above p_H, must have the highest taste for staying in India (U^D), and are the never-takers. To the immediate left of this group 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 chose to stay in India. The difference between the migrant and non-migrant compliers gives the local average treatment effect (LATE), averaged over the randomization groups. The farthest left group, below p_L, are those that have the lowest taste for staying in India, and are the always-takers. 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 $p_H = Pr(D = 1|Z = 1)$ is the share of people who migrated conditional on getting the offer.[54]

Even without extrapolating to unobserved potential outcomes, we can already see that the "untreated outcome test" proposed by Kowalski (2021) reveals little selection into migration 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.7 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.

[54] 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

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

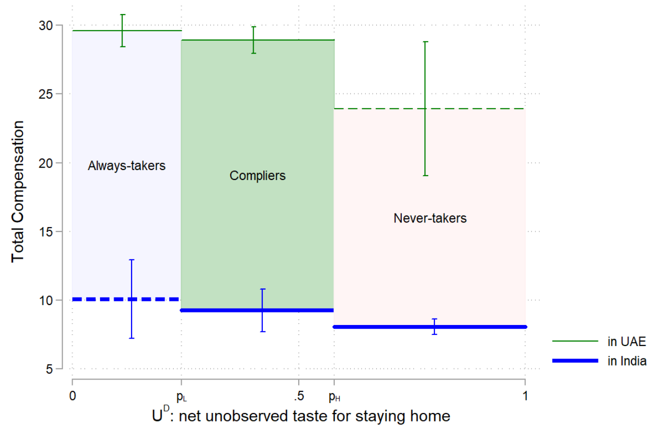
while the complier mean in India is given by

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

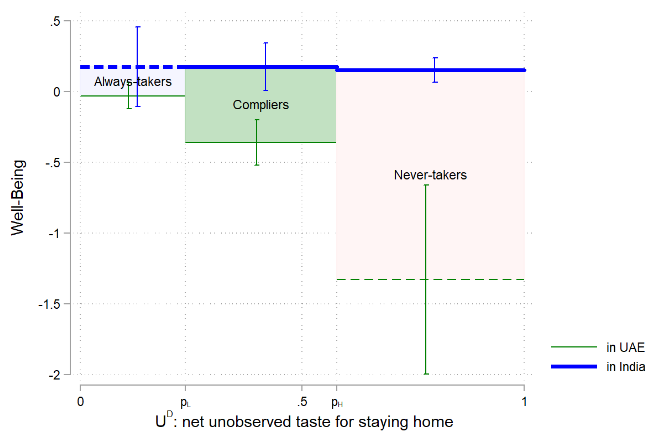
.

Figure 8: 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.

Under the further assumption of a linear MTE function, the potential outcomes for the never-takers in the UAE and always-takers in India can be extrapolated, as shown in the dashed lines in Figure 8. A linear MTE implies that the outcomes from staying in India for the always-takers can be computed from linearly extrapolating the Y^{India} of 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} of the always-takers and the treated compliers.

In Panel A of Figure 8, we see that the never-takers have slightly lower potential Y^{UAE}, measured as total compensation, than the compliers or the always-takers. As previously noted, there is very little heterogeneity in potential Y^{India} among the 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 8 suggests that while never-takers have somewhat 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. In Appendix Table A.8 we present analogous results for monthly earnings, and then sequentially incorporating in-kind benefits and monthly agent fee payments. The table shows that, under the linear MTE assumption, the source of the never-takers' lower compensation is lower monthly earnings and in-kind benefits, and there is little heterogeneity in potential agent fee payments by unobserved taste for migration.

The presence of strong tastes for staying in India (or costs of migrating to the UAE) is consistent with the results on well-being. In Panel B of Figure 8, we see that for always-takers in the UAE, they have much higher levels of well-being than the treatment group of compliers in the UAE (and this difference is significant at the 10% level) 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 8 shows that the heterogeneity is such that the workers who do not want to migrate (i.e. have the higher U^D) only have somewhat smaller pecuniary returns, but suffer large non-pecuniary costs, as proxied by falls in well-being.[55] In short, labor intermediary fees seem to be less of a barrier to migration than the distaste for UAE migrant conditions of work, even net of the wage. Relative to compliers, our MTE estimates suggest never-takers experience a full additional standard deviation fall in well-being from migrating, and still have more than 150% pecuniary returns to migrating. While we do not have information on firms' costs of increasing workers' well-being, our results suggest that improving the non-pecuniary experience of migration could increase the realized pecuniary gains, more than reforming the intermediary system.

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. 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.7, we can see that all of the groups in the experimental sample have higher

[55] We find similar, but smaller and statistically insignificant, patterns of MTEs for work satisfaction.

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 Labor Supply Elasticities from Marginal Treatment Effects

The MTE for total compensation implicitly traces out a labor supply function from India to our UAE firms. When log total compensation w is the outcome, $E[w^{UAE} - w^{India} | U^d = p]$ is the migration premium that makes workers with a probability of migrating, p, equal to their normalized taste for staying in India U^d indifferent between migrating or not. The slope of the MTE is the inverse labor supply curve, with the elasticity (with respect to the compensation in the UAE at a particular propensity to migrate p) given by $\epsilon(p) = \frac{1}{p} \times \frac{1}{\frac{-dMTE^w(p)}{dp}}$. Looking only at total compensation would imply that our never-taker workers would migrate for very small increases in wages or benefits. But once non-pecuniary effects of well-being are included in a summary measure of utility $V(w, \sigma) = w + \alpha\sigma$, so that well-being σ enters utility with α weight relative to log income, the elasticity at $p = \frac{1}{2}$ is $-2 \times \frac{\frac{dV}{dw}}{\frac{dMTE^V(p)}{dp}} = -2 \times \frac{1}{-.26 + \alpha \times (-2.23)}$.[56] Taking the specification of V as a literal measure of decision utility for treated workers (i.e. $\gamma - U^d$), the MTE estimates put bounds on α because the change in V should be 0 at every p in order to keep the marginal treated worker indifferent between migrating or not. Looking at $p = \frac{1}{2}$ we get $\alpha = 1.25$, and an elasticity of 0.65 (increasing to 1.73 at $p = 1$). The estimates of labor supply elasticities to our UAE employers narrowly bracket the Naidu et al. (2016) estimate of firm-specific new migrant recruitment elasticities for UAE firms of 1.

Migration constrained by labor supply is consistent with labor market power of destination firms in source countries. Assuming firms are setting wages constrained by a recruitment elasticity of 1, a 100% increase in UAE total compensation, holding agent fees and non-income changes in subjective well-being constant, would be efficient. Under our linear MTE assumption, this increase would induce between 65 and 173% more migration among workers with an offer, raising take-up from 50 percent to between 80 and 100%, depending on the relative value of wages vs well-being.[57]

Neighboring Qatar, facing global public criticism and some labor unrest over guest worker condi-

[56] The MTE slope estimates (for log total compensation and well-being on p) used in this calculation are in Appendix Table A.9. We chose $p = \frac{1}{2}$ because it is the halfway point in the propensity to migrate and because it is close to the actual value of p_H.

[57] One natural concern is that any gains from raising wages would be captured by labor brokers through the fees they charge. However, our evidence suggests that this is unlikely. As shown in Figure 7, there is no significant heterogeneity in take-up, compensation, or well-being by the agent fee. Further, there is a rough ratio of 1 broker for every 3 workers in a district in our data, suggesting that there is a fairly elastic and non-concentrated supply of brokers, so increases in the demand for migration would not translate into large effects on agent fees.

tions, introduced a minimum wage for guest workers in 2017, and raised it by 30% prior to the 2022 World Cup. Absent this kind of pressure, it is unclear that it is in the interest of policymakers in the UAE to support a reform that helps migrant workers at the expense of firms in the UAE. However, there are a variety of ways to solve the problem of realizing the efficient level of migration while protecting firm profits. For example, the UAE government could shift some of the surplus to firms by subsidizing recruitment through volume discounts or rebates on visas, financed out of general tax revenues. Quantifying the social incidence of reforms to guest worker programs is an important direction for future research.

5 Conclusion

In this paper, we used an experiment to show that while migration increase earnings, a narrow focus on earnings alone would miss many important effects of temporary migration. We show that guest workers to the UAE experience both increases in in-kind compensation as well higher labor broker fees, alongside falls in their subjective well-being. Quantitatively, the first two pecuniary dimensions of migration roughly cancel out in this context, leaving the earnings effect a good estimate of the overall financial return. However, given the fall in well-being that we document, the financial return is an overestimate of the overall welfare gain of migration.

Our estimates of the pecuniary returns to migration are in line with the literature. However, the similarity in the returns is perhaps surprising as the GDP per capita ratio between the UAE and India is greater than 10 in 2022, which is much larger than the ratio for Mexico and the United States (less than 4x) and other migration corridors studied in the literature such as Bangladesh-Malaysia (less than 5x), Tonga-New Zealand (around 7x), and Phillippines-Korea (less than 6x).[58] Appendix Figure A.8 shows similar returns to migration as ours in these other papers, despite the much larger gap in destination-host GDP per capita. It is also noteworthy that despite this enormous gap in GDP per capita between the UAE and India, we show that overall working conditions that migrants experience in the UAE are not significantly different from India.

Despite the large average returns to migration to the UAE, we have significant non-compliance

[58] World Bank Development Indicators at `https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD?end=2022&locations=MX-US-AE-KR-PH-IN-BD-NZ-TO-VU-HT-MY&start=1990`, accessed August 28, 2023.

with the experimental job offer, with around half of the treatment group not migrating to the UAE. In Appendix 9, we show that other papers with randomized instruments (e.g. lotteries) have found high or even higher returns to guest worker programs and also have significantly less than full take-up. This suggests that there is considerable heterogeneity in tastes or other constraints on the migration decision. We present the first estimates on the impact of migration on the subjective well-being of the migrants themselves; other papers demonstrate improvements for the well-being of households that remain behind.[59] This suggests that temporary migrants bear the brunt of the negative well-being effects of migration at least in the short-run. The split of the migration surplus within households and over time remains an interesting area for future research.

The presence of unobserved heterogeneity in tastes for migration belies views of guest program that implicitly assume a fully elastic supply of potential migrants, constrained only by destination country demand. Proponents of guest worker programs as a pathway out of poverty often assume that workers in poor countries are very willing to temporarily migrate, but visa limitations or other forces lowering labor demand prevent more individuals from developing countries from migrating. Our evidence suggests that the large earning increases that we estimate with this kind of migration is still not enough to induce migration among the pool of individuals offered the opportunity. The large number of Indians turning down the opportunity is consistent with the large loss we find in individuals' well-being associated with these moves, and is consistent with low labor supply elasticities to guest worker employers.

Guest worker programs are not just important for poverty alleviation. They can also provide a lens into fundamental causes of development, such as the stock of human capital (Hendricks and Schoellman, 2018) and the misallocation of labor. Our paper shows that the earnings effects alone presents only a partial picture of the overall guest worker system, which includes in-kind benefits, labor market intermediaries, and substantial non-pecuniary costs. Many workers in poor countries, even those interested enough in migrating to travel for an international job interview, are not willing to give up their lives in their home countries for much higher wages in the GCC. Our findings indicate that one key difference in the jobs in the UAE as compared to India is that they are far more physically taxing and the climate conditions are also harsher. Other improvements in working

[59]Stillman et al. (2015) find some evidence that when the *entire* household migrates permanently, they report ambiguous effects on subjective well-being, with lower happiness but mental health rising.

conditions or earnings may be necessary to realize more of the potential gains from international migration. While GCC-style guest worker programs may effectively redistribute income from source to destination countries, our results suggest they are less effective at redistributing welfare.

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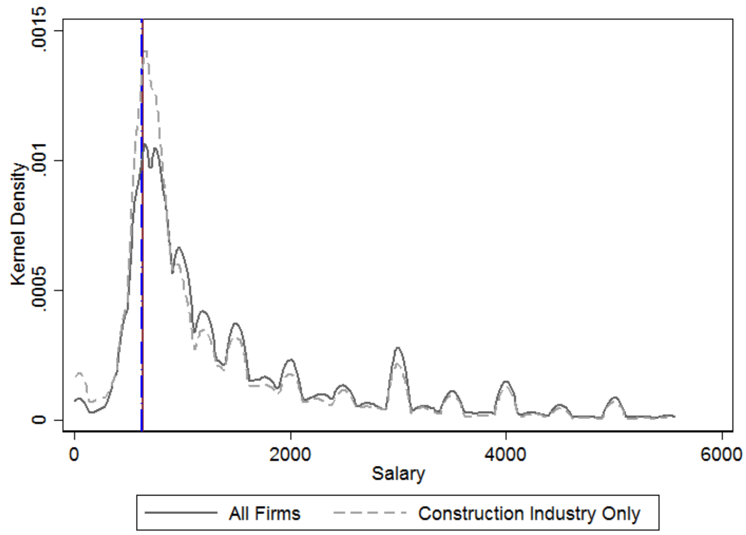
Table A.1: Baseline Summary Statistics by Treatment and Control Individuals

	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.

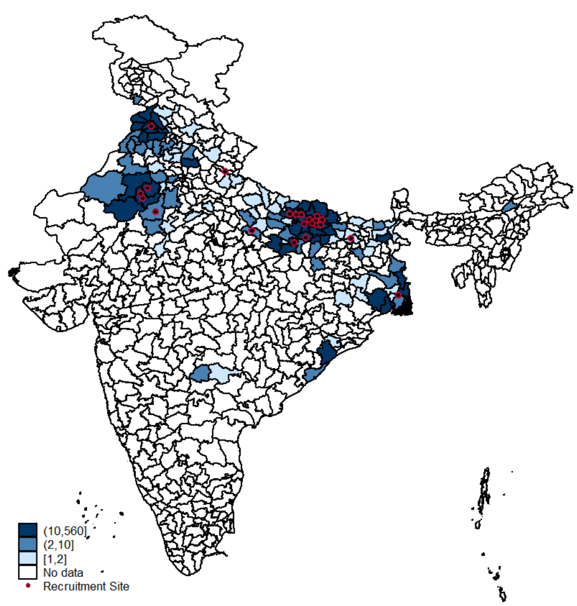
6 Online Appendix

Figure A.1: Representativeness of Experiment Firms



Notes: Using data from the universe of labor contracts in the MOL administrative data, the figure shows the distribution of average monthly contract salary (in USD) using kernel density functions for all types of firms in the solid density function and for construction firms in the dashed kernel density. The vertical dashed blue line and red solid line (which are virtually superimposed) correspond to the two firms in our analysis.

Figure A.2: Worker Home Districts



Notes: Each red dot is a recruitment location. The shaded districts show the number of workers whose home residence is in each district.

Table A.2: Baseline Summary Statistics: Attriters versus Non-Attriters

	Has Follow-up			No Follow-up			Total
	Mean	SD	N	Mean	SD	N	p-value
Age	27.90	6.30	2314	28.20	5.78	1193	0.16
High School and higher	0.41	0.49	2314	0.33	0.47	1193	0.00***
Hindu	0.75	0.43	2314	0.77	0.42	1193	0.15
Muslim	0.13	0.33	2314	0.13	0.34	1193	0.70
General Caste	0.23	0.42	2297	0.19	0.39	1184	0.00***
Scheduled Caste	0.37	0.48	2297	0.36	0.48	1184	0.39
Other Backward Caste	0.38	0.49	2297	0.44	0.50	1184	0.00***
Annual Household Income	155.12	116.96	2267	153.48	117.88	1171	0.70
Expected Annual Income UAE	305.66	259.68	2300	309.37	272.66	1179	0.70
Net Assets	881.62	1498.14	1202	929.28	1376.24	725	0.48
Ability Score	2.25	1.52	1933	2.42	1.48	1010	0.00***
Happiness	5.10	2.13	2314	5.12	2.04	1193	0.86
Locus of Control	0.87	0.76	2263	0.87	0.75	1160	0.88

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

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

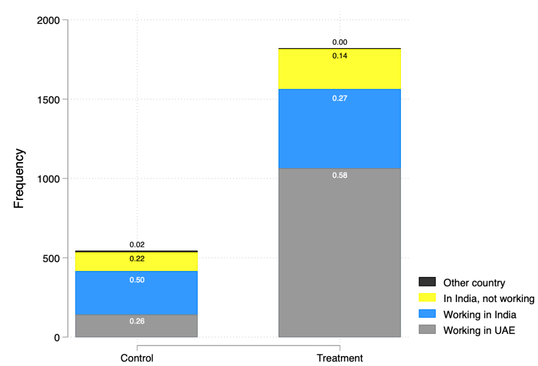


Figure A.4: Experiment Timeline

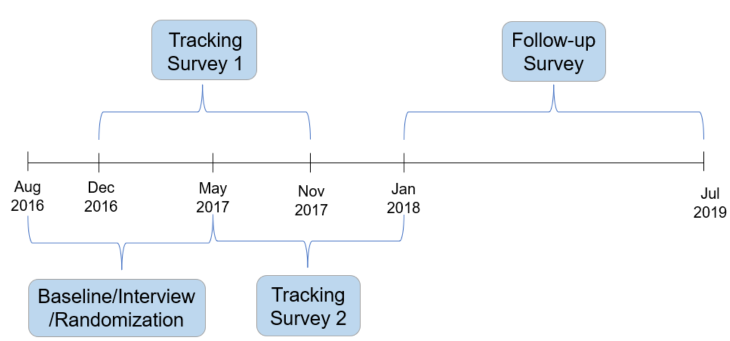
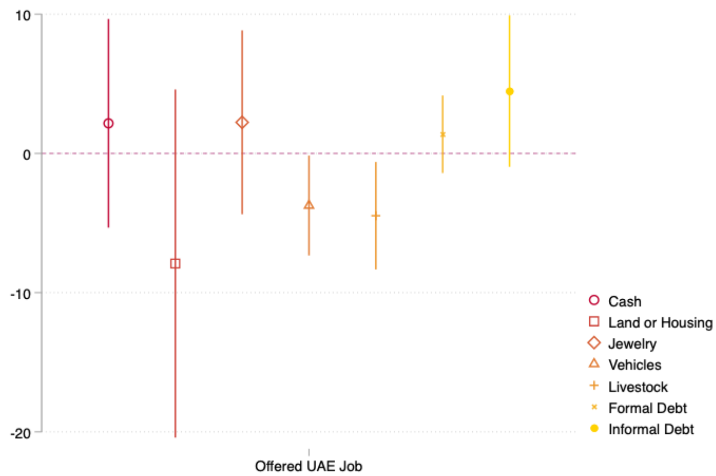
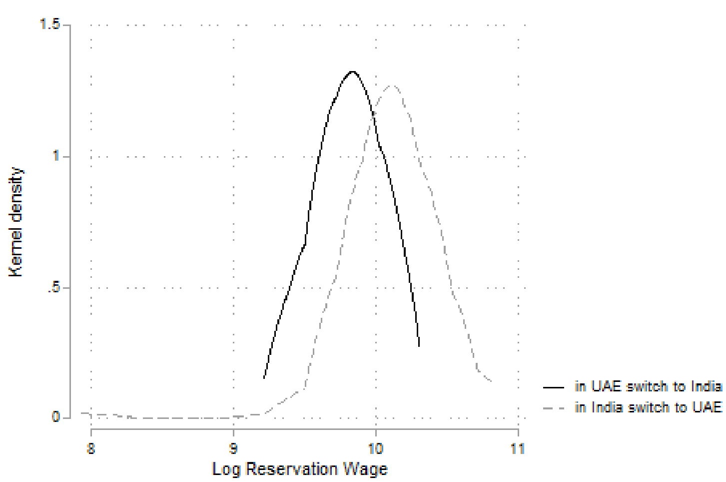


Figure A.5: Effects on Components of Assets and Debt



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 90% confidence intervals. The regressions include randomization group fixed effects

Figure A.6: 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).

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

	Has follow-up	
Number contacts	0.187***	(0.0478)
Number mobile numbers	0.0302	(0.102)
Happiness Ladder	-0.0469**	(0.0215)
Raven Score	-0.0559	(0.0435)
Locus of Control	-0.0238	(0.0649)
Age	0.00217	(0.00898)
Log HH Income	-0.0438	(0.0745)
Log Expected Income UAE	0.0238	(0.0860)
Scheduled Caste	0.552*	(0.289)
Other Backward Caste	0.412	(0.284)
General Caste	0.527*	(0.300)
Other Caste	0.944**	(0.394)
Muslim	0.173	(0.170)
High School	0.0577	(0.0902)
More than high school	0.326**	(0.152)
Interview Language not Hindi	0.649*	(0.357)
Has cell-phone	-0.748	(0.495)
Enumerator FE	Yes	
Rand Group FE	Yes	
District FE	Yes	
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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively.

Table A.4: Variable Construction and Survey Questions

Outcome	Survey Question	Variable Construction
Labor Agents		
Agent Use	Did you work with a commercial agent to get this job?	Raw variable
Arranging for Travel	Please indicate whether the employment agents assisted you in the following tasks: Arranging for travel	Raw variable
Paying for Travel	Please indicate whether the employment agents assisted you in the following tasks: Paying for travel	Raw variable
Helping with Logistics	Please indicate whether the employment agents assisted you in the following tasks: Helping with logistics (translation, filling out application forms, etc.)	Raw variable
Skills Training and Interview Prep	Please indicate whether the employment agents assisted you in the following tasks: Skills training and interview preparation	Raw variable
Applying for Passports	Please indicate whether the employment agents assisted you in the following tasks: Applying for passports	Raw variable
Applying for Visas	Please indicate whether the employment agents assisted you in the following tasks: Applying for visas	Raw variable
Paying for Visa Fees	Please indicate whether the employment agents assisted you in the following tasks: Paying for visa fees	Raw variable
Paying for Passport Fees	Please indicate whether the employment agents assisted you in the following tasks: Paying for passport fees	Raw variable
Access to Job Interviews	Please indicate whether the employment agents assisted you in the following tasks: Providing access to job interviews that you couldn't get otherwise	Raw variable
Help with Medical Screening	Please indicate whether the employment agents assisted you in the following tasks: Going through the medical screening	Raw variable
Total Agent Fee	How much is the total fee for your current job placement? (in rupees)	Raw variable
Agent Fee Paid Upfront	Of the total fee, how much is paid upfront (even if you didn't get a job offer)?	Raw variable
Agent Fee Paid Contingent	Of the total fee, how much is paid contingent on this job placement (i.e. only if you get a job offer)?	Raw variable
Migration Outcomes		
In UAE		Constructed from follow-up survey, family and friends survey, status files, Ministry of Labor data, tracking survey and tracking family and friends survey
Home District Resident	Do you live in the same district as your household?	Binary indicator for whether worker lives in household district
In UAE Experiment Firm	Now I'm going to ask you some questions about your current occupation or employment situation. What is the company name?	Binary indicator for whether worker employed at the same company as interview firm at baseline
Construction Job	What is your job title?	Binary indicator if job title is mason, carpenter, steel fixer, helper, labor or painter
Labor Market and Well-Being Outcomes		
Total Compensation	How much do you earn in this job in an average month since you have started with this firm? What is the monthly value of each benefit? Food/Housing/Other	Sum of average monthly earnings and in-kind benefits, conversion of Dirham to Indian Rupees
Monthly Earnings	How much do you earn in this job in an average month since you have started with this firm?	Conversion of Dirham to Indian Rupees
Unemployed	Are you working now, unemployed and looking for work, disabled and unable to work, retired, in school, or what? (asked in India)	Binary indicator for whether unemployed and looking for work
Work Hours	How many hours per week do you usually work at this job since you have started?	Raw variable
Prefer Fewer Hours	Would you prefer to have more or less hours of work?	Binary indicator for whether worker prefers fewer hours
Commute Time	On an average day in the last month, how long does it take you to go one-way from your home to your place of work? (in minutes)	Raw variable
Well-Being Index	How often did you experience the following feelings during the last month? 1) Enjoyment 2) Happiness 3) Stress 4) Worry 5) Anger 6) Sadness 7) Physical Pain 8) Loneliness (3-point scale from rarely to often)	Standardized weighted index from 8 items, reverse scale for items 3, 4, 5, 6, 7, 8

Work Satisfaction Index	Do you agree or disagree with the following statements? 1) The job requires a lot of physical effort. 2) The climate at the work place is comfortable in terms of temperature and humidity. 3) The job has a low risk of accident. 4) The job takes place in an environment free from health hazards (e.g., chemicals, fumes, etc.). 5) There is really too little chance for promotion on my job. 6) My supervisor often encourages me. 7) There is too much bickering and fighting at work. 8) When the firm needs overtime hours, it is my choice whether I want to work more. 9) My supervisor is unfair to me. 10) I would encourage my friends to apply for a job like mine. 11) There is a lot of uncertainty in how much work I will have each month. (5-point scale from strongly agree to strongly disagree)	Standardized weighted index from 11 items, reverse scale for items 2, 3, 4, 6, 8, 10
Financial Outcomes		
Net Assets	What is the current amount of money/cash you hold today? Include all money in bank accounts, chit funds, post office accounts, savings, cash on hand. What is the market value of your land or housing? What is the market value of your jewelry? What is the market value of all of your vehicles (include cars, motorcycles/bicycles)? What is the market value of all of your livestock? What is the total unpaid value of any loans or debts you owe in the formal sector (banks/micro finance institutions/companies etc.)? What is the total unpaid value of any loans of debts you owe in the informal sector (local moneylenders/friends/family etc.)?	Sum of asset values net of total debt
Debt	What is the total unpaid value of any loans or debts you owe in the formal sector (banks/micro finance institutions/companies etc.)? What is the total unpaid value of any loans of debts you owe in the informal sector (local moneylenders/friends/family etc.)?	Sum of formal and informal debt
Remittances Last Month	How much did you remit to your family last month?	Conversion of Dirham to Indian Rupees
Agent Fee Paid	Of the total fee, how much is already paid? (Prompt for workers in India: If you have an international job offer, please answer the following questions about the international job offer you accepted. If you have not accepted an international job offer but you had an offer, please start with the most recent overseas job offer that you have received. If you haven't received a job offer, please respond about the most recent experience searching for an international job.)	Raw variable
Attitudes and Social Network		
Rewards in India	Do you agree or disagree with the following statements? In India, people get rewarded for their effort, intelligence and skills. (5-point scale from strongly agree to strongly disagree)	Reverse scale, binary indicator above/below median
Rewards in UAE	Do you agree or disagree with the following statements? In the UAE, people get rewarded for their effort, intelligence and skills. (5-point scale from strongly agree to strongly disagree)	Reverse scale, binary indicator above/below median
Income Gap in India	Do you agree or disagree with the following statements? Differences in income in India are too large. (5-point scale from strongly agree to strongly disagree)	Reverse scale, binary indicator above/below median
Income Gap in UAE	Do you agree or disagree with the following statements? Differences in income in the UAE are too large. (5-point scale from strongly agree to strongly disagree)	Reverse scale, binary indicator above/below median
Rating Other Religion	How would you rate Indian Hindus? How would you rate Indian Muslims? (100-point scale)	Rating of Indian Muslims and rating of Indian Hindus if worker is Muslim
Rating Emiratis	How would you rate Emiratis (citizens of the UAE)? (100-point scale)	Raw variable
Importance Democracy	How important is it for you to live in a country that is governed democratically? (10-point scale from not at all important to absolutely important)	Raw variable
Closest Friend: Same Religion	What is the religion of your closest friend? (asked in India) What is the religion of your closest friend in the UAE? (asked in UAE)	Binary indicator for whether religion is the same
Closest Friend: Same Caste	Does your closest friend belong to the same caste as you? (asked in India) Does your closest friend in the UAE belong to the same caste as you? (asked in UAE)	Raw variable
All Friends: Same Language	Do you have any friends who speak another language? (asked in India) Do you have any friends in the UAE who speak another language? (asked in UAE)	Binary indicator for whether same language
All Friends: Same Religion	Do you have any friends who are of another religion? (asked in India) Do you have any friends in the UAE who are of another religion? (asked in UAE)	Binary indicator for whether same religion
All Friends: Same Caste	Do you have any friends who are from a different caste? (asked in India) Do you have any friends in the UAE who are from a different caste? (asked in UAE)	Binary indicator for whether same caste
Friends Similarity Index		Standardized weighted index from Closest Friend: Same Religion, Closest Friend: Same Caste, All Friends: Same Language, All Friends: Same Religion, All Friends: Same Caste
Team Size	How many workers are currently in the same team as you?	Raw variable
Share Same Language	How many of the workers on your team speak the same language as you?	divided by team size
Share Same Religion	How many workers on your team are Hindus? How many workers on your team are Muslims?	# Hindu co-workers if worker is Hindu or Sikh, # Muslim co-workers if worker is Muslim, divided by team size
Team Similarity Index		Standardized weighted index from Share Same Language and Share Same Religion

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 per Week	12.75***	10.75***	2,009	54.21	13.85
	(1.68)	(1.86)			
Prefer Fewer Hours	0.02	0.01	2,008	0.04	0.19
	(0.04)	(0.03)			
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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively.

Table A.6: 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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively.

Table A.7: 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	0.06	0.69	0.99
	(0.47)	(0.17)	(0.38)	(0.24)					
High School and higher	0.35	0.41	0.37	0.30	0.19	0.00	0.03	0.21	0.78
	(0.04)	(0.01)	(0.03)	(0.02)					
Hindu	0.74	0.77	0.75	0.82	0.03	0.00	0.03	0.47	0.84
	(0.03)	(0.01)	(0.03)	(0.01)					
Muslim	0.10	0.14	0.13	0.12	0.48	0.18	0.74	0.14	0.40
	(0.03)	(0.01)	(0.02)	(0.01)					
General Caste	0.20	0.22	0.22	0.13	0.05	0.00	0.00	0.74	0.62
	(0.03)	(0.01)	(0.03)	(0.01)					
Scheduled Caste	0.37	0.34	0.40	0.38	0.88	0.12	0.53	0.49	0.56
	(0.04)	(0.01)	(0.03)	(0.02)					
Other Backward Caste	0.40	0.42	0.36	0.48	0.06	0.01	0.00	0.71	0.38
	(0.04)	(0.01)	(0.03)	(0.02)					
Annual HH income	162.06	150.55	156.53	153.71	0.44	0.57	0.77	0.26	0.67
	(9.73)	(3.17)	(8.67)	(4.57)					
Expected Annual Income UAE	294.74	312.69	306.09	300.35	0.82	0.33	0.80	0.46	0.71
	(22.84)	(7.82)	(19.75)	(10.04)					
Net Assets	834.27	970.03	669.80	850.86	0.94	0.19	0.18	0.49	0.46
	(192.30)	(49.84)	(111.44)	(74.90)					
Happiness	5.62	4.90	5.10	5.05	0.00	0.08	0.75	0.00	0.01
	(0.17)	(0.05)	(0.13)	(0.07)					
Locus of Control	0.90	0.84	0.91	0.97	0.31	0.00	0.31	0.31	0.92
	(0.06)	(0.02)	(0.05)	(0.03)					
Ability Score	2.40	2.45	1.94	1.82	0.00	0.00	0.31	0.68	0.00
	(0.13)	(0.04)	(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).

Table A.8: Outcomes for Always-takers, Compliers and Never-takers Under Linear MTE

	UAE			India		
	Always-takers (1)	Compliers (2)	Never-takers (3)	Always-takers (4)	Compliers (5)	Never-takers (6)
Monthly Earnings	21.38	21.62	20.31	11.27	11.79	11.11
	(0.31)	(0.48)	(1.61)	(1.19)	(0.63)	(0.30)
...+ In-Kind Benefits	29.50	28.99	24.08	12.46	12.43	11.77
	(0.72)	(0.73)	(3.31)	(1.48)	(0.80)	(0.35)
...− Agent Fee	27.58	27.07	22.17	12.46	12.43	11.77
	(0.72)	(0.70)	(3.26)	(1.48)	(0.80)	(0.35)
Well-Being Index	-0.03	-0.40	-1.36	0.03	0.09	0.14
	(0.06)	(0.11)	(0.38)	(0.19)	(0.11)	(0.06)
Work Satisfaction Index	0.01	-0.11	-0.32	0.13	-0.00	0.07
	(0.05)	(0.09)	(0.27)	(0.27)	(0.17)	(0.06)

Notes: Column 1-6 show the mean outcomes with standard errors in parentheses. Standard errors were obtained from 500 bootstrap samples. UAE outcomes for never-takers and India outcomes for always takers are estimated under the assumption of a linear marginal potential outcomes, following Kowalski (2021).

Table A.9: Linear MTE Parameter Estimates

	Intercept	Slope
Log Total Compensation - Agent Fee	0.98	-0.26
	(0.17)	(0.32)
Well-Being Index	0.44	-2.23
	(0.35)	(0.83)

Notes: Each row shows results from a regression of the dependent variable (log total compensation or well-being) on p. Standard errors in parentheses obtained from 500 bootstrap samples. Each model includes fixed effects for randomization group.

7 Impacts on Co-Worker Networks and Attitudes

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 with whom migrants may not have interacted before, and 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. These results tie into an existing empirical literature that tests a theory advanced by Allport et al. (1954) that intergroup contact can reduce prejudice towards others.[60] Research outside of economics has considered whether interactions generated by migration affects prejudice (e.g. Gessler et al., 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.

Table A.10: Impact of Job Offer on Co-Worker Networks and Attitudes

	Unweighted Rand Group FE	Weighted All FE	N	Control Mean	Control Std.Dev
Panel A: 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)			
Panel B: 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)			

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. ***, **, * denotes significance at the 1, 5 and 10% levels respectively.

[60] Paluck et al. (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).

First, we 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 A of Table A.10 suggest that migration to the UAE corresponds to 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.

Next, given the exposure to a new country and new people, we are interested in whether attitudes about society change. 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 value of whether the respondent picked an option above the median. This allows us to examine whether 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 B of Table A.10, 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 that 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 A.10 suggest that being offered a job in the UAE corresponds to 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 et al., 2022) that finds that migration to the Gulf leads Indians to reduce their support for government redistribution.

Motivated by the presence of severe religious tensions in India, 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.[61] We construct the variable as how they rate the Indian in

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

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 A.10 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 to 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.[62] In the parsimonious specification, we see that being offered a job in the UAE corresponds to a 2.8 degree increase in their positive 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 Indians' views on democracy changes as a result of their move from their democratic home country to an authoritarian country. Acemoglu et al. (2021) show that individuals become more supportive of democracy when democracies deliver positive economic growth, and so migrants from a democratic, but poor country may become less favorable towards democracy if they have a positive experience of living in the authoritarian, but rich, UAE. Alternatively, they may be more favorable towards democracy if they dislike the experience of lacking political voice in the UAE. Specifically, in the follow-up survey, we ask how important it is 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 et al. (2022).[63]

Overall, the results suggest that migration to the UAE exposes these workers to different people than they would associate with in India. They work with more diverse teams. 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 to 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.

8 Additional Evidence from Reservation Earnings

We can obtain another estimate of 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 each 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 non-pecuniary costs of migration from India to the UAE. For comparison, we also

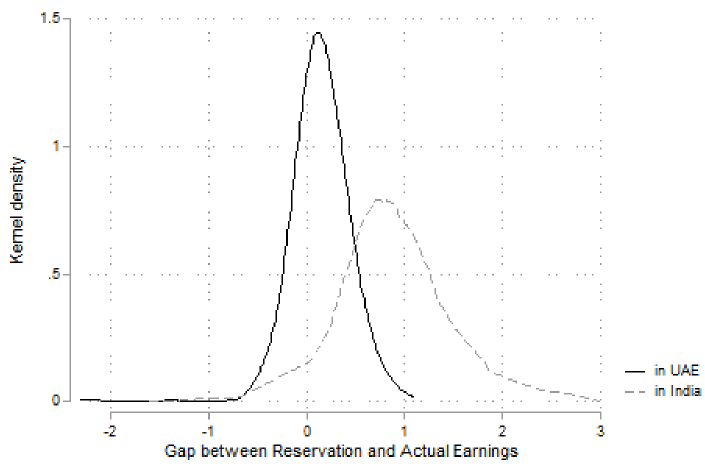
[62] Interestingly, this is very similar to but slightly higher than the way that they feel towards Indians of a different religion.

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

asked Indian workers the lowest wage they would take to migrate to the UAE, which would recover the non-pecuniary disamenity, as well as any fixed costs. If workers reported reservation wages for employment in the UAE above their current Indian wages, then this would suggest disamenities from migration to the UAE.

Formally, if the UAE workers earn 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 who have migrated to the UAE and $U_i^D = R_i^{UAE} - Y_i^{India} - F$ for workers still in India.

Figure A.7: Distribution of Disamenity from Being a Guest Worker in the UAE by Current Country of Residence



Notes: The figure shows the distributions of the gap between the logarithm of reservation earnings (to move to the other location) and the logarithm of actual 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 A.7 shows the distribution of the difference between log reservation earnings and log actual 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).[64] 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). 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, suggesting some fixed costs of migration. Those in the UAE would return to India for 20% lower earnings than what they are currently getting.

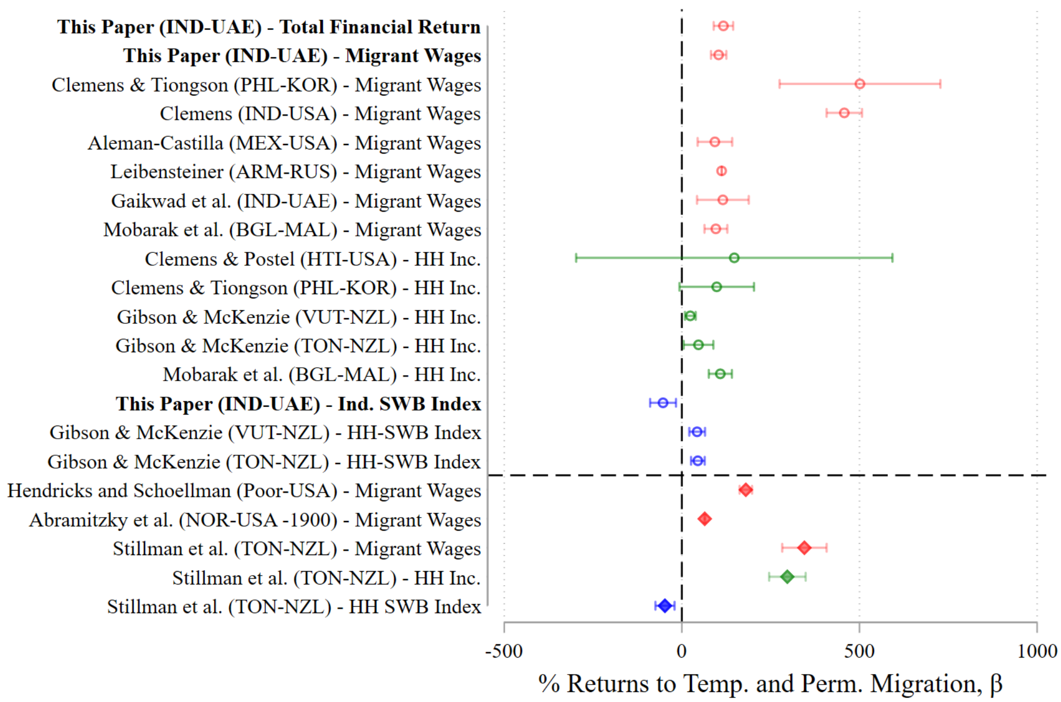
9 The Returns to International Migration

In this Appendix we discuss our estimates in the context of the literature. Figure A.8 compares our estimates to those from other experiments, retrospective household surveys of lottery winners or test passers, and non-experimental estimates. We look at migrant earnings (including non-experimental

[64] This corresponds to U_i^D. The distribution of the reservation earnings alone (not differenced with current earnings) are shown in Appendix Figure A.6.

estimates), household income (which is the outcome of interest in many of the retrospective quasi-experimental papers consider), and subjective well-being estimates. For comparison, we also show the returns to permanent migration from the literature.

Figure A.8: Returns to Temporary and Permanent Migration



Notes: This figure shows percent returns for migrant earnings (in red), household income (in green), and subjective well-being (in blue) from the literature for various migration corridors. The hollow dots above the line show effects from temporary migration literature, while the diamonds below the dotted line show the effects for permanent migration for comparison. Total financial return includes in-kind benefits and agent fees. Labels show origin-destination using World Bank country codes. 95% confidence intervals are shown.

Pecuniary Returns from International Migration: While our earnings effects are consistent with the literature, our paper differs from the literature in that we provide a more comprehensive accounting of the pecuniary returns to migration, including agent fees and in-kind compensation. While the overall effect is similar to the earnings effect, this is because the two offsetting effects: accounting for in-kind benefits raises the return, and accounting for agent fees lowers it. Figure A.8 shows existing estimates of the returns to international migration for all of migrant earnings, household income, and measures of subjective well-being, for both temporary migration programs (above the dashed line) and permanent migration (below the dashed line). Our estimates of earnings are in line with many other existing estimates in the order of 100%. Taking a precision weighted average of effects, we get that the effects of temporary migration are 166% of earnings, while the precision-weighted average effect on household income is 55%. While nowhere close to cross-country differences in GDP per capita, the returns we do see still swamp almost every other development intervention in terms of efficacy. Further, there does not seem to be a large earnings gap between temporary and permanent migration programs from the migrants perspective, although the general equilibrium incidence on both natives and migrants is likely different. **One caveat to the comparison is that different papers diverge in their use of market vs PPP exchange rates, and we follow the authors in calculating pecuniary returns.**

Non-Pecuniary Returns from International Migration: While we show negative well-being effects on individual migrants, Stillman et al. (2015) find a positive effect on *household* well-being on the households that have not migrated. Consistent with our results, Stillman et al. (2015) find a small negative effect on *household* well-being when the entire household permanently migrates (when we take a precision-weighted average of all their measures). In a long-term follow-up of the same lottery, Gibson et al. (2018) find a negative but insignificant effect on subjective well-being, and a positive and significant effect on mental health. Relative to the literature, our non-pecuniary estimates provide new insight into the potential unequal split of the costs of temporary migration within households.

Non-Compliance in Previous IV Studies: Other papers with "encouragement" designs also find imperfect take-up of migration. In Mobarak et al. (2023), 57% of the first lottery winners were still abroad at the time of survey (5 years after randomization), with only 70% ever having migrated. In Clemens (2013), the percent outside India of those accepted by the lottery after one year is only 32%, while after two years it is 58.8%. Among those rejected by the lottery, the numbers are 13% and 36.6%. So the share of "never takers" is quite large, and the ITT is only 20% of the ATE. In Clemens and Tiongson (2017), the first-stage effect on individual migrants being in Korea 3-5 years after treatment is 28.8%, with 71.2% of treated deploying to Korea at the time of test-taking. This is within a sample of potential migrants who all took a test with the aim of qualifying to migrate. Given the extremely high returns in these papers, it suggests that for a non-trivial fraction of workers who are interested in migrating, there is some other quite costly impediment for migration, consistent with our model. Clemens and Postel (2017) report monthly household income returns of close to 1400% from a Haiti-USA program, where implementation errors created some plausibly exogenous variation, but this is tempered as workers did not stay the full duration of the visa, so the annual household income effect, plotted on Figure A.8 is much smaller. The take-up of the permanent lottery in McKenzie et al. (2010) was also very incomplete, with only 54% of ballot winners actually migrating. Together, the non-compliance in randomized instrumental variables estimates are consistent with our results.