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IZA DP No. 12095

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ABSTRACT

Measuring the Spatial Misallocation of Labor: The Returns to India-Gulf Guest Work in a Natural Experiment*

'Guest workers' earn higher wages overseas on temporary low-skill employment visas. This wage effect can quantify global inefficiencies in the pure spatial allocation of labor between poorer and richer countries. But rigorous estimates are rare, complicated by migrant self-selection. This paper tests the effects of guest work on Indian applicants to a construction job in the United Arab Emirates, where a crisis exogenously influenced job placement. Guest work raised the return to labor by a factor of four, implying large spatial inefficiency. Short-term effects on households were modest. Effects on information, debt, and later migration were incompatible with systematic fraud.

JEL Classification: F22, J6, O12, O16, O19

Keywords: income, human capital, migration, labor, mobility, guest work, India, gulf, construction, worker, selection, migrant, temporary, visa, wage, education, crisis, low-skill, unskilled, credit, exploited, naive, regret, slavery, trafficking, debt, coerced, cheated

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Over 18 million people work overseas on temporary low-skill employment visas. These 'guest workers' are comparable in number to the entire labor force of Argentina or Poland.[1] Such migrants exhibit average wages several times higher than many workers in their typically-poor home countries. If those observed wage gaps represent the real effects of migration on workers' economic productivity, guest work offers one channel for large global efficiency gains from the spatial reallocation of labor (Benhabib and Jovanovic 2012; Kennan 2013) as well as unparalleled opportunity for low-income households (Djajić 2014). And the world's 582 bilateral guest worker agreements signed since 1945 (Chilton and Posner 2018) could be considered a mechanism for greater global economic efficiency and opportunity for the poor.

But these ideas have been challenged in two ways. First, there is little evidence about the self-selection of temporary migrants, who have "often been ignored in the economic literature on migration" (Dustmann and Görlach 2016). An unknown portion of the observed wage gaps between guest-workers and non-migrants could arise from self-selection on intrinsic human capital, making the gaps mostly illusory as indicators of spatial misallocation inefficiencies (Abramitzky et al. 2012; Hendricks and Schoellman 2018). Second, policy advocates warn that guest workers' wage gains could be misleading indicators of their welfare, reporting that guest work contracts exhibit widespread asymmetric information, fraud, coercion, and other abuses (e.g. HRW 2006; Bauer and Stewart 2013). Much of the scant empirical literature on welfare effects of guest work either considers small-scale "best practice" programs (Gibson and McKenzie 2014) or lacks a credible counterfactual.

This paper uses a natural experiment to estimate the economic effects of construction guest work in the United Arab Emirates (UAE) on thousands of workers across India and their families. An unexpected crash in the UAE construction sector in late 2008 caused a sharp and persistent decline in the probability that any given hired Indian worker departed for work in the UAE. Three years later, survey teams across India reached out to the households of the full universe of Indians who had been hired by a major UAE construction firm from early 2008 to early 2009—several months before and after the crash. Under the assumption that each worker's precise job-application date was otherwise uncorrelated with economic outcomes three years later, this allows estimation of the Local Average Treatment Effect of UAE guest

[1] Lower bound on worker counts compiled in Appendix A2.

work on economic outcomes in those households in 2011.

The paper tests several necessary conditions for ignorable treatment assignment, such as testing the null hypothesis of no correlation between survey response and application date (in the universe) and no correlation between baseline traits and application date (in the sample). It argues with a simple model that self-selection of guest workers will be typically intermediate in this and related settings. The estimates test for direct effects on workers' wages, and for signs of naïveté or fraud, such as *ex-ante* misinformation and *ex-post* indebtedness.

The paper considers temporary labor migrants in order to investigate the pure economic effects of reallocating labor across space, from India to the Gulf. Permanent migration, in contrast, is shaped by family reunification, foreign study, investment for later generations, public benefits, and varying labor force participation—features largely absent from guest work. The study employs three strategies to minimize self-selection and isolate causal relationships. First, basic theory discussed below suggests that temporary migrants should exhibit less pronounced self-selection from poor countries than permanent migrants. The second is its sampling universe, exclusively comprising Indian men who were willing and able to *successfully* apply for a UAE guest work job. The third is its use of an economic shock that quasi-randomly allocated, among those successful applicants, final placement in the UAE.

The contribution of the paper is primarily empirical. It presents a unique causal estimate of the household-level economic effects of the opportunity to perform guest work in one of today's largest guest work corridors, between South Asia and the Gulf Cooperation Council countries, which appears in principle to offer large gains (Naidu et al. 2017; Weyl 2018). Prior rigorous causal estimates of the effects of guest work arise from smaller migration corridors more heavily regulated to protect guest workers (McKenzie and Yang 2015; Clemens and Tiongson 2017), consider historical settings (Dinkelman and Mariotti 2016), or evaluate a shock to the earnings of existing guest workers, not a shock to guest work participation itself (Yang 2006, 2008). Prior rigorous estimates of migrant self-selection, essential to unbiased estimates of the effect of migration, focus on permanent migrants rather than guest workers (e.g. Chiquiar and Hanson 2005; McKenzie et al. 2010; Abramitzky et al. 2012); a notable exception is Bazzi (2017). A lesser contribution of this paper is its theoretical argument. It posits that, within the intermediate self-selection one might expect from a country with high poverty and binding capital constraints to investing in migration (Chiquiar and Hanson 2005; Hanson 2006), a simple model predicts that such self-selection will be relatively less positive for guest workers than permanent migrants.

The evaluation finds that placement in the UAE for guest work causes a 25 percentage-point increase in the probability that an applicant is employed (anywhere) when observed three years later, and among employed applicants, causes a fourfold increase in earnings. This very large effect is on the same order as the wage returns to university education, within India, relative to illiteracy. The causal wage gain of 1.3–1.4 log points is similar to the purely observational wage gap of 1.3–1.5 log points between observably identical Indians in the UAE versus India, implying intermediate self-selection of guest-work migrants on unobserved determinants of wages. That is, observational wage gaps in this setting are a roughly accurate indicator of large inefficiencies in the spatial allocation of labor.

The short-term (three year) effects on the worker's household are generally modest: there is no evidence that guest work alters labor force participation, entrepreneurship, or indebtedness for the rest of the household. Remittances sent by the guest worker while abroad typically just offset the wages in India that he forgoes by his absence, and guest work does not cause substantial changes in the ownership of durable goods other than refrigerators. There is little evidence of systematic fraud or naïveté about guest work among these households: Direct experience of guest work does not cause a substantial downward revision of their impressions of earning power, nonwage working conditions, or living conditions in the UAE.

The paper begins by discussing the empirical setting and observed wage differences between the UAE and India, in section 1. It proceeds to argue theoretically that temporary migrants tend to self-select intermediately on observed and unobserved determinants of earnings, in section 2. Section 3 describes the natural experiment and section 4 probes the strength and validity of the instrumental variable. Section 5 presents the empirical results, and section 6 summarizes and interprets them.

1 Background: Temporary foreign workers in the UAE

Over 90% of workers in the UAE are temporary workers from overseas, primarily South Asia (Naufal 2015, 1611). They have been attracted by long-term economic growth since the 1980s, driven primarily by oil production but with a growing complement from services—especially finance and tourism—and some manufacturing. The country revolutionized its infrastructure during this period, hiring very large numbers of foreign workers in construction and related occupations. The country's overall employment rose from 288,051 in 1975 (with 42,762 UAE nationals) to roughly 4 million in 2010 (with about 211,000 UAE nationals). Construction accounted for almost half of all UAE employment in 2008, compared to 19% in trade services and 11% in manufacturing. Over half of total employment growth between 2007 and 2008 occurred in construction, almost entirely foreign workers. The UAE is a major migration destination for Indians, and is the leading destination for people from the state of Kerala (Zachariah and Rajan 2009, 35).

What are the economic effects of this guest work on the people who do it? An imperfect starting point is simply to compare the wages of Indians in the UAE to the wages of Indians in India, in nationally-representative data. Consider stacking microdata on Indian workers in both countries in a single dataset, and regressing the log wage on an indicator variable for presence in the UAE. This is done in the first column of Table 2. The unconditional observed wage difference for Indians, between the UAE and India, is 2.8 log points, a wage multiple of 15.9.

Now condition on a rich set of indicator variables for age, sex, education, and urban residence, all interacted with the indicator for presence in the UAE.[2] The results are in columns 2–5 of

[2] The age dummies ι^{a} are for the set of ten quinquennial ranges: 15–19, 20–24, 25–29, ..., 60–64, with below 15 and above 64 omitted from the sample. The schooling dummies ι^{s} are for the set of eight categories of education completion: "Illiterate", "Read & Write" (but no schooling), "Primary", "Preparatory" (some secondary but no secondary degree), "Secondary", "Above secondary", "University", and "Above University". For female $\iota^{\mathrm{f}} = 1$, for urban $\iota^{\mathrm{r}} = 1$. The vast majority of Indian workers in the UAE, by standards meaningful in India, work in 'urban' settings, so all Indians in the UAE are assumed 'urban'. The regression equation is expressed with Hadamard and tensor products as $\ln w = \boldsymbol{\alpha}'\boldsymbol{\iota}_{\boldsymbol{w}} + \sum_k \mathbb{1}'_{W+1}\Big(\boldsymbol{\beta}_{\boldsymbol{k}} \circ \big(\boldsymbol{\iota}_{\boldsymbol{w}} \otimes \boldsymbol{\iota}_{\boldsymbol{k}}\big)\Big)\mathbb{1}_K + \varepsilon$, where $\boldsymbol{\iota}_{\boldsymbol{w}}$ is a $(W+1)\times 1$ vector of worker-type dummies $[1 \;\; \iota_i \;\; \iota_u \;\; \iota_e]'$, here with $W = 3$; $\boldsymbol{\iota}_{\boldsymbol{k}}$ is a $K \times 1$ vector of dummies for levels of trait k: $[\iota_1^k \;\; \iota_2^k \;\; \ldots \;\; \iota_K^k]'$ where $k \in \{a, s, f, r\}$ and K is the number of categories in trait k; $\boldsymbol{\alpha}$ is a $(W+1) \times 1$ vector and $\boldsymbol{\beta}_{\boldsymbol{k}}$ is a $(W+1) \times K$ matrix of coefficients to be estimated; $\mathbb{1}_c$ is a $c \times 1$ vector of ones; and ε is an error term. Rupee wages w are

Table 2. For observably identical workers—males age 30–34 with some secondary education (but no secondary degree)—the wage multiple between the UAE and India is 4.9 (a difference of 1.4 log points) relative to urban areas of India, or a ratio of 7.9 (a difference of 1.9 log points) relative to rural areas. If we restrict the sample to broadly relevant occupations (construction and related trades, drivers, security guards), the wage ratio is 4.5 for urban Indians and 5.6 for rural Indians (a log difference of 1.3 or 1.5, respectively).

These observational estimates suggest that UAE jobs have the potential to cause very large increases in earnings for low-skill Indian workers and their households. The wage gap between a low-skill Indian in the UAE and a low-skill urban Indian in India is greater than the wage gap between a university-educated Indian in India and an *illiterate* Indian in India.[3] If these observed differences could be interpreted as causal relationships, the wage returns to migration would be greater than the wage returns to any feasible investment in education by most poor people growing up in India. This would suggest very large global economic efficiency returns to marginal expansions of guest work.

But these observational wage differences could be biased estimates of the causal relationship between migration and wages, to the extent that guest worker migrants self-select on unobserved correlates of wages. In the counterfactual case that Indians in the UAE had been unable to migrate, they might be in the upper (lower) portion of the distribution of wages for observably identical workers in India. This would result in upward (downward) bias to the ratios in Table 2 due to positive (negative) selection on unobserved traits. Moreover, estimates of the pure effect of migration on individual workers' wages need not capture the full effects of migration and remittances on income of the worker's household. The following section explores formally how self-selection of migrants into guest work—relative to non-migrants, or permanent migrants—might alter the interpretation of the results in Table 2 and shape migrant households' financial decisions.

measured at exchange rates, unadjusted for India-UAE price differences, given that the analysis focuses on Indian workers and ∼85% of the earnings of Indian temporary workers in the UAE are spent in India (Joseph et al. 2018) at Indian prices. The analysis includes wage income only, and omits workers with zero wage income. It thus compares *employed* wage-workers between countries. It omits non-wage benefits, the most important of which in this setting is housing provided by UAE employers.

[3] In the regression in col. 2 of Table 2, the coefficient on university educated (base group: no educ.) is 1.394.

Self-selection of Indian migrants into temporary migration according to *observed* skill is broadly positive, but much weaker than for permanent migration. Table 2 shows the proportion of Indian adults (age ⩾25) with various levels of education and residing in India, the UAE (where most are temporary migrants), and the United States (where most are permanent migrants), all in nationally-representative datasets circa 2008–2010. The proportion with a high school degree or less is 87% in India, 63% in the UAE, and 16% in the United States. That is, for these important migration corridors, self-selection on observable skill is very high for permanent migration; selection is closer to intermediate but still positive for guest work.

2 Self-selection and the theoretical effects of guest work

Basic theory suggests that guest work should differ from permanent migration in its effects on migrant self-selection, income, and financial decisions. These predictions emerge from an extension of the standard model of migrant self-selection.[4] Special patterns of self-selection in temporary migration arise because temporary migrants can have different skills, different returns to skill, and different purchasing power than permanent migrants.

In this model, workers with relatively low skill self-select out of temporary migration because they cannot borrow enough to pay the costs of migration, and remain at home. But workers with relatively high skill likewise self-select out of temporary migration, because the returns to *permanent* migration are higher. This occurs if the overseas returns to high-skill migrants' skills depend on spending a longer time overseas—such as to acquire skill recognition, build professional networks, and adapt their training. Relatively low-skill migrants get low returns to such investment in overseas human capital, and prefer to return home and spend their overseas earnings at (low) home-country prices.

In other words, simple theory predicts that workers who self-select into temporary migration will be those from the middle of the skill range. This in turn implies that observational wage gaps between migrants and non-migrants are less biased as estimators of the returns to temporary migration than for (more positively selected) permanent migration.

[4]Developed by Roy (1951), Borjas (1991), Chiquiar and Hanson (2005), and Hanson (2006).

2.1 Selection and sorting of temporary migrants on observed skill

Suppose a worker chooses between working in the home country (H) and working abroad, temporarily (T) or permanently (P). The per-period nominal wage at location j (real wage w inflated by price level Π) is set by a fixed effect ν and the return δ to an observable trait s such as schooling, both specific to country and duration, by $\ln\left(w^j \Pi^j\right) = \nu^j + \delta^j s$. Letting $\pi^j \equiv \ln \Pi^j$, the real wage is

$$\ln w^j = \nu^j - \pi^j + \delta^j s, \quad j \in \{H, T, P\}. \tag{1}$$

Equation (1) becomes informative with inequality constraints on the parameters. Normalize home-country prices to unity ($\Pi^H \equiv 1$), and assume that permanent migrants spend most of their income at (much higher) destination-country prices, while temporary migrants spend most of their income at home-country prices ($\pi^P \gg \pi^T \gtrsim \pi^H \equiv 0$).[5] Suppose that the per-period unskilled nominal wage does not depend greatly on duration ($\nu^T \approx \nu^P$) and define the pure country effect on real wages as $\mu^j \equiv \nu^j - \pi^j$, which is thus higher at the destination for temporary than permanent migrants. Assume also that the country effect of migration on nominal wages exceeds the price difference regardless of duration ($\nu^j - \nu^H > \pi^j$, $j \in \{T, P\}$), thus

$$\mu^T > \mu^P, \;\; \mu^T > \mu^H, \;\; \mu^P > \mu^H. \tag{2}$$

Now assume that the return to s is lower for temporary than for permanent migrants—for example because the substance or recognition of skilled migrants' training can only be partially transferred between countries in the short term, but skilled migrants can adapt their training and acquire skill recognition in the long term (Dustmann and Görlach 2016). And assume, as is standard in the literature, that the return to s is higher in the home country, where it is scarce, than abroad. Thus

$$\delta^T < \delta^P, \;\; \delta^T < \delta^H, \;\; \delta^P < \delta^H. \tag{3}$$

Assumptions (2) and (3) determine patterns of migrant self-selection and sorting. Workers solve $\max_{j \in \{H,T,P\}} \ln w^j - \ln\left(w^H + \Theta^j\right) \approx \max_{j \in \{H,T,P\}} \ln w^j - \ln w^H - \theta^j$, but they are wealth

[5] This assumption is supported by theory and evidence in e.g. Djajić (1989); Dustmann (1997); Dustmann and Mestres (2010); Dustmann and Görlach (2016). In particular, Indian temporary workers in the UAE spend ~85% of their earnings in India (Joseph et al. 2018).

constrained in paying migration costs (Rapoport 2002; Orrenius and Zavodny 2005; Hanson 2006). Suppose that the costs of migration (Θ^T, Θ^P) are expressed in time-equivalent units by $\theta^T \equiv \Theta^T/w^H$ and $\theta^P \equiv \Theta^P/w^H$, letting $\Theta^H \equiv \theta^H \equiv 0$. Workers can only borrow a fraction $1-\gamma$ of the migration cost and must pay the rest from wealth $\rho + \sigma s$, assumed positive and increasing with schooling $(\rho, \sigma > 0)$. This implies intermediate self-selection on observable s for both temporary and permanent migration,[6]

$$\frac{\gamma\Theta^j - \rho}{\sigma} \equiv \underline{s}^j < s < \bar{s}^j \equiv \frac{\mu^j - \mu^H - \theta^j}{\delta^H - \delta^j}, \quad j \in \{T, P\}, \tag{4}$$

and migrants choose permanent migration if and only if

$$s > \tilde{s} \equiv \frac{\left(\mu^T - \mu^P\right) + \left(\theta^P - \theta^T\right)}{\delta^P - \delta^T}. \tag{5}$$

Migration conditions (4) and (5) define migrants' self-sorting and selection on observable trait s, summarized in Figure 1.[7] While migrants in general exhibit intermediate selection on observable s, temporary migrants are negatively selected among them, since

$$E\left[s \,\middle|\, \underline{s}^T < s < \tilde{s}\right] < E\left[s \,\middle|\, \underline{s}^T < s < \bar{s}^P\right]. \tag{6}$$

Thus, all else equal, a destination country that allows only temporary work visas will receive self-sorting migrants with lower s than if both temporary and permanent migration were allowed. But even for such a destination, temporary migrants are positively self-selected on s if the origin country has sufficiently low average observed skill, that is if

$$E\left[s \,\middle|\, \underline{s}^T < s < \tilde{s}\right] > E\left[s\right]. \tag{7}$$

[6]From credit constraint $\rho + \sigma s > \gamma\Theta^j$ and migration condition $\mu^j + \delta^j s - (\mu^H + \delta^H s) > \theta^j$, $j \in \{T, P\}$.

[7]Figure 1 portrays the nondegenerate case in which both temporary and permanent migration can occur, requiring $\bar{s}^P > \bar{s}^T$, $\bar{s}^P > \underline{s}^P$, and $\bar{s}^T > \underline{s}^T$. Large, simultaneous temporary and permanent migration flows have been observed in many migration corridors with large origin-destination income differentials and few policy barriers (e.g. Bandiera et al. 2013). The figure moreover shows a case in which $\bar{s}^T > \tilde{s} > \underline{s}^P$, but the predictions below follow under other orderings as well with immaterial modifications.

2.2 Selection and sorting on unobserved skill

So far this is a deterministic model of selection and sorting across observable skill groups. It can be easily extended to a stochastic model of selection and sorting on *unobserved* skill differences within observed skill groups.

Let $\hat{s}(s)$ signify unobserved skill, randomly distributed across workers of observed skill level s, with mean zero. The wage return to unobserved skill $\hat{s}$ is $\hat{\delta}$. Define the deterministic component of the nominal wage $\hat{\nu}^j(s) \equiv \nu^j + \delta^j s$. The real wage (1) for any given level of observed skill s becomes $\ln w^j(s) = \hat{\nu}^j(s) - \pi^j + \hat{\delta}^j \hat{s}(s)$. This yields by identical reasoning a pair of conditions analogous to (4) and (5) for selection and sorting on *unobserved* skill, and analogous critical values $\big(\hat{\underline{s}}(s), \hat{\bar{s}}(s), \hat{\bar{\bar{s}}}(s)\big)$, within each level of observed skill s.

Some predictions are similar to those for observed skill, others are not. Within an observed skill group s, all else equal, temporary migrants exhibit negative self-selection on unobserved skill relative to migrants in general since

$$E\big[\,\hat{s}(s)\,\big|\,\hat{\underline{s}}^T(s) < \hat{s}(s) < \hat{\bar{\bar{s}}}(s)\big] < E\big[\,\hat{s}(s)\,\big|\,\hat{\underline{s}}^T(s) < \hat{s}(s) < \hat{\bar{s}}^P(s)\big], \tag{8}$$

analogously to (6). Thus if a destination allows only temporary migration within an observed skill group, migrants self-sort to that destination more negatively on unobserved skill than if both temporary and permanent migration were allowed. But it is unclear whether temporary migrants to such a destination with observed skill s are positively or negatively selected on unobserved skill. The unobserved positive selection condition analogous to (7) is

$$E\big[\,\hat{s}(s)\,\big|\,\hat{\underline{s}}^T(s) < \hat{s}(s) < \hat{\bar{\bar{s}}}(s)\big] > 0, \tag{9}$$

which may or may not hold, depending on parameters. Among temporary workers at a given observed skill level who self-sort to such a destination, self-selection on unobserved skill could be positive, negative, or intermediate—regardless of average observed skill at the origin.

2.3 Effects on wages

Measuring the effects of migration on workers' wages requires measuring the degree of selection on observables and unobservables. In fact we can define migrant selection in terms of different estimates of the effect of migration on wages.[8]

Let the destination-origin real wage ratio $G^j(s,\hat{s})$ represent the gain to migration of type j assuming that migrants' average levels of observed and unobserved skill are respectively s and $\hat{s}$. That is, $G^j(s,\hat{s}) \equiv e^{\mu^j+\delta^j s^j+\hat{\delta}^j \hat{s}^j}/e^{\mu^H+\delta^H s+\hat{\delta}^H \hat{s}}$, $j \in \{T,P\}$, where $s^j, \hat{s}^j$ are respectively the observed and unobserved skills of migrants that choose j. The unconditional observed ratio between migrants' destination-country wages and non-migrants' origin country wages is $G^j(s^H,\hat{s}^H)$, while the wage ratio for observably identical migrants and non-migrants is $G^j(s^j,\hat{s}^H)$. Selection on observable skill for migration type $j \in \{T,P\}$ can be measured by the ratio

$$R_o^j \equiv \frac{G^j(s^j,\hat{s}^H)}{G^j(s^H,\hat{s}^H)} \gtrless 1 \quad \Longleftrightarrow \quad s^j \lessgtr s^H. \tag{10}$$

That is, if the destination-origin wage ratio for observably identical workers is greater (less) than the simple unconditional wage ratio, this is a necessary and sufficient condition for negative (positive) selection on observable skill. Selection on unobservable skill for migration type $j \in \{T,P\}$ at observed skill level s can likewise be measured by the ratio

$$R_u^j(s) \equiv \frac{G^j(s^j,\hat{s}^j(s))}{G^j(s^j,\hat{s}^H(s))} \gtrless 1 \quad \Longleftrightarrow \quad \hat{s}^j(s) \lessgtr \hat{s}^H(s). \tag{11}$$

That is, if the destination-origin wage ratio for observably and unobservably identical workers is greater (less) than the wage ratio for observably identical workers at skill s, this is a necessary and sufficient condition for negative (positive) selection on unobservable skill. Roughly speaking, if the effect of migration on income appears to diminish as we control for observable differences between migrants and non-migrants, there is positive selection on observables; if the effect further diminishes as we control for unobservable differences as well, there is positive selection on unobservables. Because selection and sorting differ between temporary and

[8]This is a departure from the selection literature, which arose explicitly from a concern among non-migrants about declining immigrant quality (Douglas 1919; Borjas 1991, 33). A different formulation of selection conditions is better suited to the goal of measuring the effects of migration on migrants.

permanent migrants, we can expect the wage gains to differ as well.

2.4 Summary of predictions

The model suggests that migrant self-selection and sorting, and the resulting effects of migration on wages and finances, can differ systematically between temporary and permanent migrants. The relative real gains to low-skill temporary migration can be larger than for other types of migration—both because the lower-skill workers that self-select into temporary migration have a lower reserve option at home, and because temporary movement allows them to earn in a high-price country and spend in a low-price country. This simple model predicts less positive self-selection for temporary migrants than for permanent migrants (equation 6).

Credit constraints mean that temporary migrants could exhibit positive selection on observed skill from low-skill countries of origin ($R_o^T < 1$), but exhibit intermediate selection on unobserved skill within observed skill groups ($R_u^T(s) \gtrless 1$). The true effect of migration on wages is difficult to measure without a strategy to control for observed and unobserved differences between migrants and non-migrants.

In contrast to large effects on wages, theory predicts ambiguous effects of temporary migration on basic financial decisions such as consumption and savings. On one hand, standard life-cycle permanent-income models (Modigliani and Brumberg 1954; Meghir and Pistaferri 2011, 782) predict that a large but transitory shock to income will have little effect on consumption. On the other hand, 'temporary' migration may produce more sustained rises in income if workers expect to repeatedly work abroad on temporary visas, which could give the income shock more of a permanent character and a greater effect on current consumption. The same basic theory predicts substantial borrowing, especially by lower-skill temporary migrants, to finance migration itself.

3 Method: A natural experiment in the UAE

The empirical method here seeks to measure the effect of UAE guest work on several thousand Indian households, and thereby measure the degree of selection on unobserved wage determinants (10) that could bias the estimates in Table 2. This is achieved by two means.

First, the sampling universe of the survey is a group that has already taken several actions to self-select into Gulf guest work. It comprises all successful applicants from India to a leading UAE construction firm during the period in question. This substantially restricts the potential scope of self-selection within this group relative to the general population. All of the workers surveyed had an initial interest in overseas work, had an interest in UAE construction work specifically, learned about this job opportunity, expressed their interest by physically traveling to one of four recruitment centers across India, applied for the job, and possessed the attributes needed to persuade the firm to hire them. It leaves only two important margins for self-selection into migration: choosing to decline any competing overseas job offers, and choosing not to remain in India.

Second, to address the remaining margins for self-selection into migration, the empirical method relies on a *force majeure* that greatly and persistently altered the probability that any given hired worker ended up traveling to and working in the UAE. At the end of August 2008, the global financial crisis burst a speculative bubble in the Dubai property market. The proximate cause was a collapse in the price of the UAE's leading export, petroleum, interrupting debt service in the highly leveraged construction sector. This sudden and unforeseen event caused severe delays in or cancellation of hundreds of large construction projects. For this reason, small differences in the application date for hired foreign construction workers caused large differences in the probability that the hired worker was in fact able to travel to the UAE and begin work, for reasons plausibly independent of the workers' observed or unobserved determinants of earnings.

Enacting this research design required linking three sources of data on Indian workers. The first is firm data. The sampling universe comes from a major UAE construction firm that provided basic information for all workers recruited and selected at its four Indian recruitment centers during a set period. It comprises all workers recruited and selected in Delhi and Mumbai between June 1, 2008 and May 31, 2009, and those in Chennai and Ramnad between March 1, 2008 and April 30, 2009. This yields initial age, occupation, skill level, religion (a Muslim indicator variable inferred from name), and contact information for 7,480 workers across India.

The firm dataset was linked to novel survey data collected when survey teams attempted to visit the contact address for all 7,480 workers between August 25 and November 4, 2011.[9] The survey teams used the contact information provided on the job application form to physically locate the households of 58.7% of all applicants (4,393 households) across nine states. Their spatial distribution is shown in Figure 2. Among these households, 62.1% (2,727 households) had a knowledgeable adult in the applicant's family available and willing to complete an hour-long interview. Finally, both the firm data and survey data were matched at the worker level to administrative records from the UAE Ministry of Labor indicating whether or not the worker had been physically present in the UAE to receive a three-year work visa ("labor card").[10]

4 Validity of the natural experiment

The natural experiment can be informative under two sets of assumptions. The first is that the construction crash substantially, monotonically, and persistently affected the probability of UAE guest work for applicants in the sampling universe.

This was the case, shown in Figure 3. In both panels of the figure, the quantitative indicator of the crash is an index of the Dubai Fateh spot oil price (scaled so that the price on May 1, 2008 = 100). Figure 3a shows, in the sampling universe, a moving average of the probability that an Indian job applicant on each date ended up arriving in the UAE to work at some point

[9] Except four pilot interviews, conducted July 30 to August 4, 2011, in Delhi and Chennai.

[10] The administrative records are excellent, but not perfect, indicators of presence in the UAE. First, limited numbers of workers might choose to depart the UAE before their work contracts end. This is uncommon, as both employers and employees incur fixed initial costs and it is in the interests of both to have workers complete the contract. Second, limited numbers of workers may have come to the UAE on a different passport than the one listed in their job application (if it was lost, stolen, or expired), so that I could not match their UAE employment records to the job application. This is also uncommon, as Indian passports for adults are valid for 10 years.

prior to November 2011. Figure 3b shows, in the final survey sample, a moving average of the probability that the surveyed household reported that the applicant had ever worked in the UAE (at the time of the survey or beforehand). Both in the universe and the sample, the crash exerted a large influence on the probability of UAE guest work by the applicant three years later.[11]

The second assumption is that there is no other channel by which a substantial correlation could arise between economic conditions in the UAE in 2008–2009 and economic outcomes for the workers' households three years later. This could be violated if the global financial crisis had produced a large and concurrent labor market shock in India, and the effects of that shock had persisted through 2011. But no such generalized shock occurred. The Indian labor market, quite unlike the United States and other other major world labor markets, was little affected by the crisis. The unemployment rate in India modestly *fell* during this period.[12]

This assumption could also be violated by nonresponse bias. For example, if crisis-affected migration behavior altered the survey teams' success in contacting each household or persuading it to participate, this could in principle generate correlation between the oil price on the application date and observed or unobserved determinants of later economic outcomes. The first column of Table 3 tests for a relationship between the oil price and survey response. It shows, for the sampling universe, a regression of the oil price as of the job application date (in 2008–2009) on an indicator variable for whether that applicant's household successfully yielded a completed survey (in 2011). Applicants whose households yielded a completed survey applied on days where the oil price was one point higher on the 100 point scale, a difference that is neither statistically nor economically significant.

The assumption could furthermore be violated if migrants self-selected into applying to the job, in different time periods, according to traits that could differentially affect their economic outcomes three years later. The second column of Table 3 regresses, in the sampling universe, the oil price at the application date on several predetermined traits of the applicant listed on

[11] After April 2009, when the economic situation had stabilized, several delayed construction projects recommenced, and placements of approved workers into the UAE rose sharply.

[12] The World Bank estimates that the unemployment rate in India was 4.1% in 2007, 4.1% in 2008, 3.8% in 2009, and 3.5% in 2010.

his job application. There is some modest imbalance: Applicants age 25–40, applicants from Tamil Nadu and Maharashtra, and applicants from rural districts tended to apply on days where the oil price was a few points higher than it was when other applicants applied.

The third column carries out the same regression on the applicants whose households yielded a completed survey, and exhibits a very similar modest but statistically significant imbalance on the same traits. The similarity between the second and third columns of Table 3 limits the scope for self-selection into survey response according to unobserved determinants of economic outcomes. For example, a high degree of selection into survey response according to unobserved skill is less plausible in the absence of substantial selection on observed skill.

Due to these imbalances, though they are minor in magnitude, all known predetermined traits of each household's job applicant are included as controls in the regressions that follow.[13]

5 Results

The natural experiment permits empirical estimates of the effects of UAE guest work on a range of individual-level and household-level economic outcomes. Each set of results below begins with an Ordinary Least Squares (OLS) regression of the outcome on a dummy for migration. It is followed by two sets of instrumental variable (IV) results, with the oil price on the day of application instrumenting for migration. The first IV estimator is standard two-stage least-squares (2SLS), which reports the heteroskedasticity-robust Montiel-Pflueger (2013) F-statistic to test the null hypothesis of weak instruments. The second IV estimator is the dummy endogenous variable (DEV) model due to Heckman (1978), which is more efficient than 2SLS under the assumption that dichotomous treatment is well-specified by the probit model.

Each table presents estimates using two different definitions of 'treatment'. The first is whether guest work is in progress at the time of the interview, the second is whether guest work has

[13] The Appendix shows a breakdown of the migration-by-application-date curve in the sampling universe from Figure 3a according to the survey attempt outcome. The relationship between the oil price on the application date and the propensity of applicants on that date to migrate is similar whether one considers only the households that provided a completed survey, only households that could not be located, or only households that were absent or declined to be surveyed.

occurred at any time prior to or at the time of the interview. This is done to illuminate the potential for the results to be shaped by self-selection into return migration.

5.1 Effects of guest work on the job applicants

Table 4 presents the core results of the paper: estimates of the effect of guest work on individual applicants' wages and employment.[14] In the first row, the outcome is ln wage and treatment is defined as current presence in the UAE. This is the relationship between UAE presence and ln wage conditional on employment. The OLS coefficient, 0.946, is substantially and statistically significantly less than the OLS coefficients of 1.3–1.5 obtained when simply comparing observably identical workers in nationally representative data (Table 2). By equation (11), this suggests that relative to the broader Indian population, within observed skill groups there is positive selection into applying for UAE jobs.

The IV coefficients, however, are 1.3–1.4 and statistically significant at the 1% level, substantially above the OLS coefficient of 0.946. The estimate $\hat{\beta}_{\text{IV-2SLS}}$ coefficient estimate is 1.381 with a 95% confidence interval of [0.398, 2.36].

We can place an informative bound on this estimate if the exclusion restriction is violated mildly and monotonically. Suppose, plausibly, that workers with relatively better unobserved determinants of job prospects in India were somewhat less likely to hold out for UAE placement when the UAE crisis was at its worst. This would tend to generate a negative correlation between labor market outcomes in 2011 and the oil price instrument, by a mechanism other than the pure effect of the instrument on migration itself. The monotonicity of this unobserved self-selection would make the IV coefficient estimate a lower bound on the true value: $\hat{\beta}_{\text{IV-2SLS}} > 1.381$. The lower end of the two-sided 95% confidence interval would shift from 0.398 to 0.813.[15]

[14] All regressions include controls for the predetermined traits of each household's applicant reported in Table 3. The instrumental variable is the Dubai Fateh oil price on the day of the job application in 2008–2009. If a worker is in the UAE, his wage is converted to rupees at ₹13.1 per Emirati dirham, the average mid-market exchange rate that prevailed during the bulk of the survey period (September–October 2011) from XE.com, accessed February 1, 2015. "Employed" means that the worker did any work for pay at all, including self-employment. Wage and earnings regressions here omit those self-employed in a home-based family business or farm (11% of those working age).

[15] Using the method of Nevo and Rosen (2012) implemented by Clarke and Matta (2018).

The difference between the IV and OLS coefficients suggests that relative to the subpopulation of successful job applicants, there is negative selection into actually arriving in the UAE for guest work. That is, it suggests that—while the Indians who apply for these jobs and are able to get hired tend to possess better unobserved determinants of job prospects than average observably identical Indians—among those hired, those who actually arrive in the UAE tend to possess worse unobserved determinants of job prospects than the rest.

This is corroborated by the results for employment, in the second row of the table: Applicants present in the UAE in 2011 are 19 percentage points more likely to be employed (OLS estimate), but presence in the UAE *causes* them to be 25 percentage points more likely to be employed (IV-2SLS and IV-DEV estimates). That is, among the positively-selected Indians who apply for and receive the job offer, applicants with relatively worse job prospects in India for unobserved reasons tend to eventually arrive in India. If one assumes the same mild and monotonic violation of the exclusion restriction as above, Nevo-Rosen bounds imply $\hat{\beta}_{\text{IV-2SLS}} > 0.253$ with the lower end of the two-sided 95% confidence interval at 0.148.

The estimated combination of positive selection into application and hiring, followed by negative selection into UAE arrival, yields overall intermediate selection on unobserved determinants of labor-market outcomes relative to the Indian population as a whole. The wage effect of guest work as estimated by this natural experiment on a subpopulation, at least 1.3–1.4 log points, is similar to the purely observational OLS estimates of 1.3–1.5 in the nationally representative data of Table 2. The IV estimates imply that UAE guest work causes a successful applicant at this firm to experience a wage increase of 3.81–3.98 times the wage he would otherwise receive, or more. Given that $\sim$85% of Indian guest workers' earnings in the UAE are spent in India (Joseph et al. 2018), this implies that guest work causes an increase in real wages in the hundreds of percent even after adjusting the small portion of UAE-spent wages for higher prices in the UAE.

5.2 Effects of UAE work on Indian workers' households

Table 5 tests for effects of guest work by the applicant on other working-age adults who reside in the applicants' households—not including the applicant himself. The first three rows of the table test for effects on an indicator of employment, an indicator of receiving any wages, and the ln wage among wage-recipients. There are no evident statistically significant effects of guest work by the applicant on non-applicants' outcomes.

The next two rows of the table test whether the applicant's migration causes migration by other working-age members of the household. The estimates suggest a positive effect of 5–7 percentage points in the probability that another working-age household member migrates for guest work, though these estimates are only statistically significant at around the 10% level. In sum, guest work by the applicant does not appear to systematically affect labor force participation or earnings by other household members, and there is suggestive evidence that it causes a small increase in the probability that other household members migrate for guest work.

Table 6 tests for household-level effects of the applicants' guest work on overall household monthly income, remittance receipts, and expenditures. These outcomes include only the income and expenditures of household members present in India, and are measured in per-capita terms in order to be more informative: A change of zero in the household's total food expenses, for example, could arise from the composed effect of a decline in the number of people to feed (when the applicant is absent) and a rise in the amount eaten by each remaining person. The latter effect is isolated by conversion to per-capita quantities.[16]

The first row of Table 6 indicates that guest work by the applicant may cause households—counting only members in India—to be smaller by more than one person, perhaps reflecting delayed marriage and/or procreation by applicants who depart for guest work. In the second row, households with guest workers have 18% higher incomes per capita, but the IV coefficients suggest that this is not caused by the applicant's guest work. In the third row, the IV coefficient estimates imply that guest work causes a household's probability of receiving any remittances to rise by 54–61 percentage points. But in the fourth row, guest work does not cause a significant increase in the amount of remittances conditional on receiving any remittances (though this result is far from a precise zero, given the weak instrumentation implied

[16]Respondents reported food expenditures in the previous month. Other expenditures—quality of life, medical, education, and durables—were reported as cumulative values over the past year and converted to monthly values by dividing by 12.

by a low Montiel-Pflueger F statistic).

That is, guest work by the applicant greatly increases remittances at the extensive but not intensive margin, and net of removing his own India-based income from the household, does not systematically raise household income per capita overall. These estimates are compatible with guest workers sending their families, on average, roughly enough to replace the wages they would have contributed to the household had they remained in India—but no more. The rest of the portion not spent in the UAE they appear to retain control of, either repatriating savings by hand or transferring to their own India-based account.

The remaining rows of Table 6 test for effects on expenditures per capita. The fifth row OLS coefficient implies that households with applicants in the UAE spent 22% more than those without applicants in the UAE. The IV coefficients are positive and larger but not statistically precise, suggesting that the OLS coefficient may not arise mostly from selection bias, but not permitting a precise estimate. The coefficient estimates on food, quality of life, medical, and education expenditures likewise suggest positive effects of roughly 20% or more, but do not permit a precise estimate. The IV coefficients on durable-goods expenditures suggest that the positive OLS estimate could arise from selection bias (but are marred by weak instrumentation suggested by a low Montiel-Pflueger F statistic).

There is only and weak and suggestive evidence of a positive effect of guest work on business activity and durable-goods ownership. Table 7 presentes estimated effects on an indicator of whether or not the household receives any profits from business activity, the amount of business revenue, or the amount of business profit. The positive IV coefficient of 0.15–0.20 on the indicator of business activity is not statistically significant at conventional levels, with a p-value of 0.21–0.22. The IV coefficients do not indicate a positive effect of guest work on business income. In Table 8 the IV coefficient estimates imply a positive effect of 36–52 percentage points on the probability of owning a refrigerator, with a p-value of 0.06–0.07, but there is no distinguishable effect for any other major household asset.[17]

[17] A positive effect on refrigerator ownership would not necessarily conflict with the absence of an effect on durable goods expenditures in Table 6, given that the latter is measured only over the course of the year leading up to the survey. That is, durable goods expenditures were reported for roughly the year between September/October 2010 and September/October 2011, depending on the exact date of each household's interview. Refrigerators caused to be purchased by guest work migration could have been purchased between March 2008 and August

Tests were also conducted to attempt to assess the effects of guest work on schooling of school-age children of the job-applicant, showing no statistically significant beneficial or detrimental effects. But instrumentation was extremely weak (with Montiel-Pflueger F-statistics between 0.6 and 2.9) suggesting that those estimates may be too severely biased to be informative. They are reported in the Appendix.

5.3 Effects on information and indebtedness

The literature reports widespread concerns that South Asian guest workers in the Gulf earn less and experience greater difficulty than they believed they would, finding their wages insufficient to pay debts for labor brokerage and travel. Zachariah et al. (2003, 166) report that "nearly one-fifth of the Indian migrants [in the UAE] have not received the same job, wages, and non-wage benefits as stipulated in their work contracts," and Zachariah and Rajan (2009) find that large fractions of earnings by Indian migrants to the Gulf are spent on debts incurred to travel. Rahman (2011) reports that many Bangladeshi migrants to Saudi Arabia do not earn enough to pay back debts that they incurred to travel there, suggesting either naïveté or fraud.

One approach to assessing households' information about UAE work is to compare the views held by households with and without direct exposure to that work. Each survey respondent in India was asked to assess typical wages in the UAE for a man from that household, working conditions in the UAE ("apart from his earnings . . . such as safety, enjoyment of the work, difficulty of the work"), and living conditions in the UAE ("such as housing and food"). Respondents rated working and living conditions on a 1 to 5 scale of increasing quality relative to conditions in India.[18] If any man in the household was in UAE at the time of the survey, the respondent was asked about his current wage, working, and living conditions. If no man in the household was in UAE at the time of the survey, the respondent was asked about what those conditions would be if "a man from this household might have the opportunity to work in the UAE."

2010.

[18] That is, 1 = "Much worse than India"; 2 = "Worse than India"; 3 = "Similar to India"; 4 = "Better than India"; 5 = "Much better than India".

Figure 4 compares household's ratings of living and working conditions according to whether or not the household had *ever* (at the time of the survey or before) had a male member working in the UAE. The responses in red show answers given by households with no direct experience of working in the UAE. The responses in green are either reports of actual conditions by a male member of the household currently in the UAE, or reports of hypothetical conditions that would be faced by such a male member given by households where a male member has directly experienced the work. The household's subjective ratings of non-wage working conditions (Figure 4a) and living conditions (Figure 4b) are very similar, whether or not the household has directly experienced UAE work. Households with direct experience of UAE work have a slightly reduced tendency to rate working and living conditions there as "much better" than India, but an increased tendency to report conditions there as "better" than India. There is no meaningful difference between the groups in the tendency to report "worse" or "much worse" conditions.

Migrants could, of course, self-select based on information sets, so Table 9 reports IV estimates following the same format as prior tables. In the first row, the outcome for each household is either a report of the true wage of a male household member who is currently in the UAE, or if there is no such member, a guess about what that wage would hypothetically be. In the lower half of the table, where treatment is defined as having ever had a household member in the UAE, the OLS coefficient implies that households with direct experience of UAE guest work believe that a man from their households could earn about 10% less than households without direct experience of UAE guest work. The IV coefficients, however, are positive and not statistically distinguishable from zero. The next two rows test for effects on non-wage working conditions and living conditions. The IV estimates are positive, only marginally significant for working conditions (p-value 0.09), and not significantly different from zero for living conditions.

These results do not provide evidence of a substantial effect of direct guest work experience on households' basic information about the wage and non-wage amenity values of UAE guest work. This is incompatible with a typically high degree of information asymmetry, among these successful job applicants, between those who get their information from personal experience and those who get it from others.

Table 10 reports estimates of the effect on households' borrowing and debt. In the first row, the outcome is an indicator variable for whether the household reports recent borrowing for any purpose ("Did your Household borrow money in the last 3 years?"). In the second row, the outcome is an indicator for whether the household borrowed specifically to assist in migration. The IV-2SLS estimates are positive but not statistically significant; the IV-DEV estimates are positive and similar in magnitude but highly statistically significant. The latter imply that guest work caused households to be 11 percentage points more likely to have borrowed, of which the large majority (9 percentage points) was to assist in migration. The OLS and IV-DEV coefficient estimates put the average increased borrowing at roughly ₹20,000 (about US$400) during the previous 3 years.

But that induced borrowing appears, on average, to have been repaid by 2011. In the OLS coefficients, migration is not associated with a greater likelihood of holding any debt, or a greater amount of debt. The IV-2SLS coefficients are negative and the IV-DEV coefficients positive but close to zero, both statistically indistinguishable from zero. These estimates are not compatible with a large average effect of guest work on household indebtedness three years later.

6 Conclusions

This paper has presented estimated effects of guest work on thousands of successful Indian applicants to a UAE construction firm and on the applicants' households. The effects are identified using quasi-random allocation of exposure to guest work induced by the 2008 UAE construction-sector crash.

Guest work causes a 25 percentage point increase in the probability that an applicant is employed (in either country) when observed three years later, and causes the wages of an employed applicant to rise by a factor of four. This causal relationship is similar to the effect that would be estimated by a purely observational comparison of employed workers' wages between observably identical Indians in the UAE and in India, in nationally representative data. That is, this group of Indian guest workers exhibits intermediate self-selection on unobserved determinants of wages. This overall intermediate selection comprises both positive selection into applying for and receiving the job offer, and conditional on that, negative selection into actually arriving in the UAE for work.

The wage effect of spatially reallocating workers into Gulf guest work—a multiple of four—is very large. It is similar to the wage gap *within* India, in nationally representative data, between university-educated workers and otherwise similar illiterate workers. The real-wage effect of guest work is of the same order as the nominal-wage effect, given that the vast majority of guest workers' earnings are spent in India.

This suggests that the large observed wage differences between Indians in the UAE versus India do not arise mostly from differences in intrinsic human capital, whether observed or not. The principal cause of the observed wage gap is the locations of the workers—comprising extrinsic determinants of their economic productivity such as capital, technology, institutions, externalities from others' human capital, and agglomeration economies (Clemens et al. 2019). This implies that guest work can be a channel for substantial marginal increases in global economic efficiency, greatly raising the economic product of labor simply and exclusively by changing its location. It also suggests that guest work raises workers' incomes far more than most known aid interventions designed to raise income. Such interventions, when successful, might raise incomes of the poor in India and elsewhere by 10–40% (e.g. Blattman et al. 2014; Banerjee et al. 2015b), while many such interventions appear to have little effect at all (e.g. Banerjee et al. 2015a).

The short-term (three-year) effects of guest work on the rest of the household are modest. There is no evidence of reduced labor-force participation by other working-age adults in the household. Guest work causes a rise in remittances at the extensive but not intensive margin, remittances that roughly replace the lower income that the guest worker would have been earning in India, rather than constituting a net rise in income for the portion of the household that remains in India.[19] Guest work appears to cause a substantial increase in the households' ownership of refrigerators, but not of other durable assets.

[19]This does not count savings personally repatriated by the migrant.

The evidence as a whole does not support contentions that guest work systematically and typically causes regret among the workers who do it. Firsthand experience of guest work does not cause households to substantially reduce their subjective impressions of UAE guest work—how much a construction worker can earn in the UAE, what his nonwage working conditions are like, or what his living conditions are like—relative to households with no direct experience of UAE guest work. Guest work causes substantial increases in household borrowing, mainly to support migration itself, but does not cause increases in household indebtedness three years later. Guest work by one member of a household does not cause reductions in the probability of guest work by other household members. To the contrary, there is marginally statistically significant evidence that guest work by the applicant raises the probability of guest work by other household members. None of these are compatible with the average worker's experience being one of naïvté or fraud, either with regard to earnings, job safety, or housing.

It is important to clarify what these findings do and do not imply for other workers, especially in other countries. None of these results translate automatically to all Indian workers in the UAE, since the whole sample of workers used here were job applicants through a single construction company. That company is, however, typical of several like it, is very large, and recruits all over India (Figure 2). The results likewise to not translate automatically to other migrant origin countries or other migrant destination countries. That said, the economic background of people from other origin countries such as Pakistan doing similar jobs in the UAE is rarely radically different; and economic conditions of construction workers in other Gulf countries such as Qatar and Kuwait do not differ radically from those in the UAE.

One lesson applicable to other settings is that migrants, certainly including guest workers, self-select in different ways at different margins, often on unobserved traits that co-determine economic outcomes of interest. A full understanding of the economic effects of migration requires probing beyond purely observational wage differences. But international wage gaps in the hundreds of percent are very difficult to explain mostly by self-selection on such unobserved traits. In the important South Asia-Gulf corridor, the evidence here suggests that little of the observational wage gap can be thus explained.

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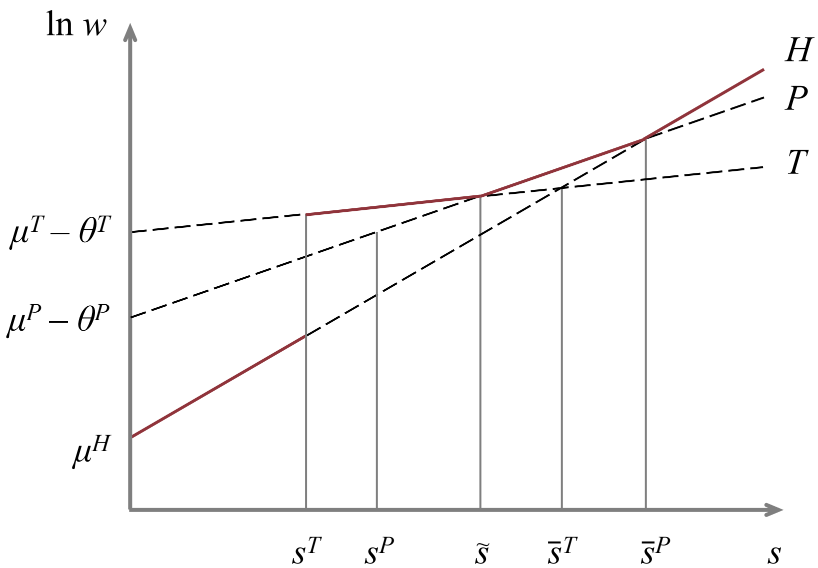
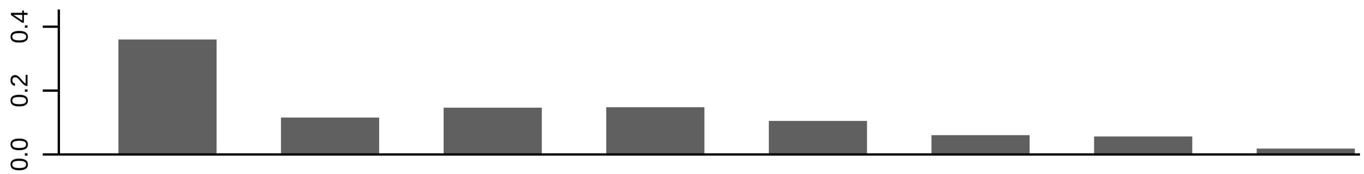
Figure 1: Selection and sorting in temporary migration

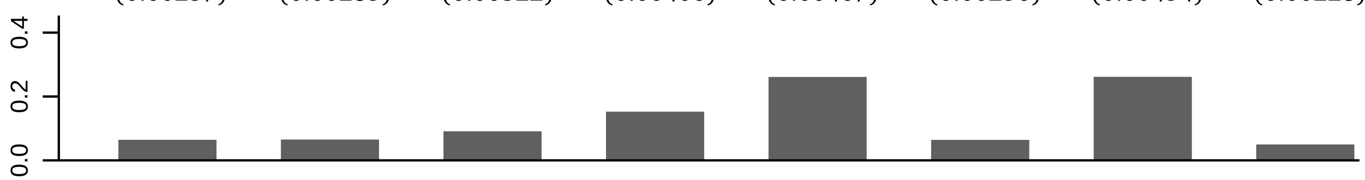


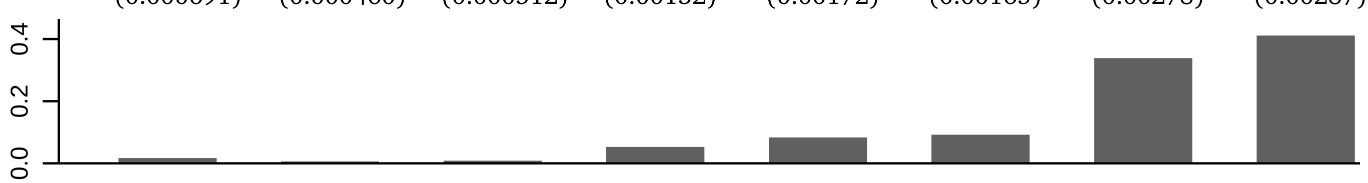
The solid red line shows wages for optimizing workers at each skill level. H shows the ln wage for workers who self-select to remain in the home country, P for those who self-select to migrate permanently, and T for those who self-select to migrate temporarily (guest workers). μ is the real wage in each location, and θ is time-equivalent migration costs. $\tilde{s}$ is the level of skill above which migrants choose permanent migration over temporary, while the $\bar{s}$ and $\underline{s}$ show the range of intermediate self-selection on skill for each type of migration.

Table 1: Proportion with each level of educational attainment: Indian adults in India, UAE, and USA; nationally representative

	None	Pre-primary	Primary	Pre-sec.	Secondary	Pre-univ.	University	Postgrad.
India	0.359	0.114	0.145	0.147	0.103	0.0592	0.0550	0.0171
	(0.00146)	(0.000954)	(0.00109)	(0.00110)	(0.000937)	(0.000715)	(0.000666)	(0.000408)
Indians in UAE	0.0631	0.0639	0.0898	0.151	0.260	0.0630	0.260	0.0486
	(0.00237)	(0.00285)	(0.00322)	(0.00406)	(0.00467)	(0.00256)	(0.00454)	(0.00228)
Indians in USA	0.0158	0.00483	0.00730	0.0516	0.0821	0.0909	0.337	0.410
	(0.000691)	(0.000460)	(0.000512)	(0.00132)	(0.00172)	(0.00165)	(0.00278)	(0.00287)







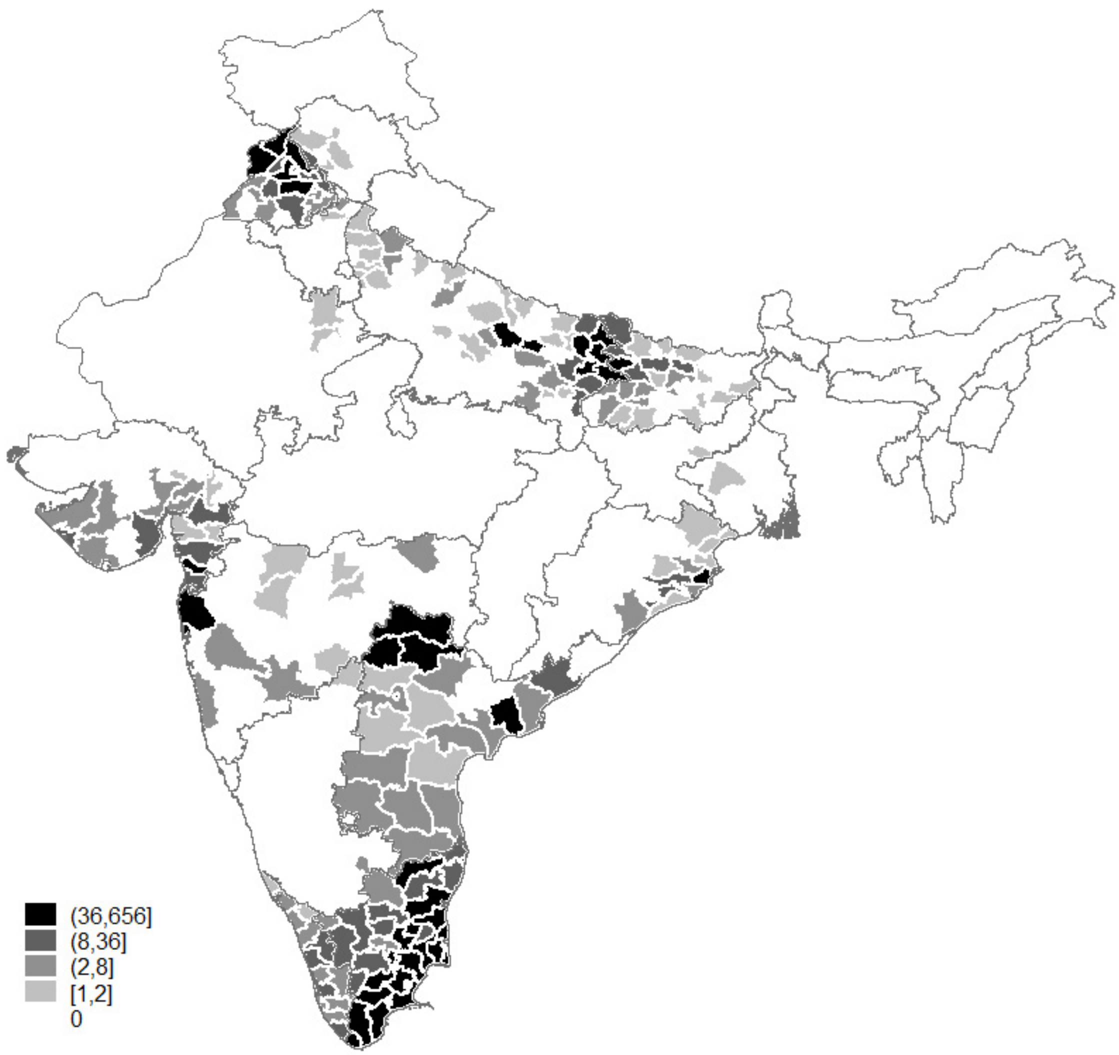
Proportion with level of highest educational attainment among Indians resident in each country shown, age 25+. Standard errors in parentheses below each proportion. "India" shows data from the nationally-representative India National Sample Survey 2008–2009, all India residents. "UAE" from the nationally-representative UAE Labour Force Survey 2008, Indian nationality. "USA" from the pooled 2008–2010 American Community Survey in Ruggles et al. (2010), country of birth India. Weighted by sampling probability weights.

Table 2: Observational wage differences in nationally-representative data, 2008

Traits X:	Any	Male age 30–34, some secondary educ.			
Occupations in sample:	All			Relevant only	
India region:	*All*	*Urban*	*Rural*	*Urban*	*Rural*
Conditional mean wages, rupees per month					
Indians in India: $\mathrm{E}\left[w_i \middle\| X\right]$	2,154	3,710	2,279	3,704	2,994
	(10)	(51)	(30)	(89)	(69)
Indians in UAE: $\mathrm{E}\left[w_u \middle\| X\right]$	34,169	18,021	18,021	16,788	16,788
	(490)	(455)	(455)	(874)	(874)
Ratio of conditional mean wages, UAE versus India					
$\mathrm{E}\left[w_u / w_i \middle\| X\right]$	15.86	4.86	7.91	4.53	5.61
	(0.24)	(0.14)	(0.23)	(0.26)	(0.32)
Log difference of conditional mean wages, UAE versus India					
$\mathrm{E}\left[\ln w_u - \ln w_i \middle\| X\right]$	2.764	1.376	1.863	1.258	1.471
	(0.015)	(0.089)	(0.089)	(0.150)	(0.149)
Obs. of Indians in India, N_i	92,709	92,709	92,709	18,513	18,513
. . . of which rural	*35,047*	*35,047*	*35,047*	*8,235*	*8,235*
Obs. of Indians in UAE, N_u	5,811	5,811	5,811	1,190	1,190

India data from 2008–2009 India National Sample Survey (NSS), UAE data from 2008 UAE Labor Force Survey (LFS). Dirhams converted to rupees at average exchange rate prevailing during the NSS data collection period (July 2007–June 2008, ₹10.99/dirham)—not adjusted for purchasing power, given that ∼85% of workers' earnings are spent in India (Joseph et al. 2018). Regressions weighted by relative sampling weights. Standard errors (in parentheses) are reported in each case for the Wald test that the exponentiated linear combination of coefficient estimates yielding each conditional mean (or ratio of means) is unity. Columns 2–5 show predicted wages based on coefficient estimates from the regression equation in footnote 2 for 30–34 year-old male with less than secondary education completed ("preparatory", no secondary degree); values N show number of observations in the underlying regression. "India region: urban" means that estimates compare Indians in UAE to Indians in urban India; "India region: rural" means that estimates compare Indians in UAE to Indians in *rural* India. "Relevant" occupations are principally construction and related trades, drivers, and security guards—defined and background on the datasets given in Appendix subsections A3.1 and A3.2.

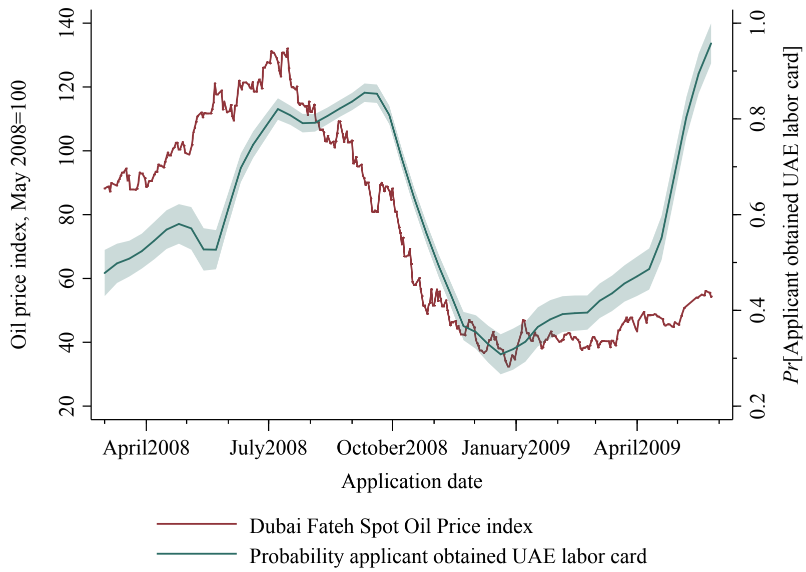
Figure 2: Location of the household sampling universe in India



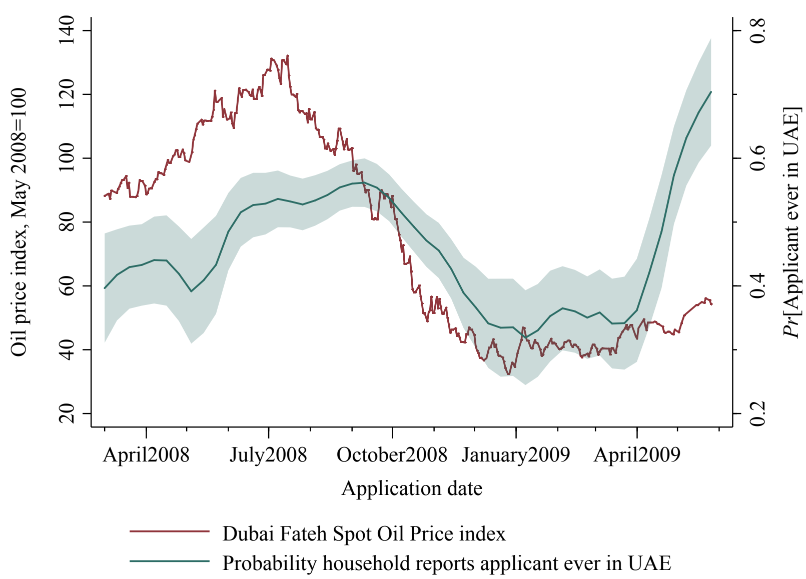
Density map shows number of households in the sampling universe within each district of India whose addresses were sufficiently complete to locate the dwellings.

Figure 3: Persistent effects of the crash on guest work migration

(a) *Sampling universe: UAE administrative records on probability of applicant arrival*



(b) *Survey sample: Household reports that applicant ever worked in the UAE*



Shaded band shows 95% confidence interval on local regression, Epanechnikov kernel, bandwidth 15 days, degree 0. Dubai Fateh Spot Oil Price is the price per barrel for light sour crude oil extracted from Dubai, scaled to an index such that the price on May 1, 2008 equals 100. Obtaining UAE labor card requires physical presence in the UAE.

Table 3: Correlation between the instrument and survey response or predetermined traits

Dep. var.:	Dubai Fateh Spot Oil Price Index		
Coverage:	Universe		Sample
Survey completed	1.088 (0.714)		
Age 25–29		2.719 (0.912)	2.464 (1.481)
Age 30–34		3.113 (1.084)	4.299 (1.751)
Age 35–39		2.875 (1.251)	2.584 (2.077)
Age 40–44		0.392 (1.732)	1.261 (2.948)
Age $\geqslant$ 45		−2.984 (2.746)	−3.138 (5.435)
Semiskilled		2.388 (1.228)	2.638 (2.061)
Skilled		2.644 (1.244)	1.581 (2.092)
Muslim		0.217 (0.733)	0.0584 (1.245)
Tamil Nadu		4.285 (1.151)	7.972 (5.244)
Uttar Pradesh		−0.225 (1.496)	0.902 (5.504)
Andhra Pradesh		1.544 (1.785)	5.124 (5.714)
Punjab		−0.770 (1.793)	−0.446 (5.769)
Bihar		−0.299 (1.927)	2.111 (5.884)
Maharashtra		7.323 (2.084)	12.00 (5.797)
Gujarat		−3.265 (2.366)	−6.980 (6.270)
Orissa		1.282 (2.605)	4.707 (6.486)
Kerala		−1.173 (3.211)	1.860 (7.111)
Rural district		1.975 (1.066)	4.690 (1.607)
Constant	80.65 (0.434)	72.68 (1.936)	68.09 (5.704)
N	7479	7441	2717
Adjusted R^2	0.000175	0.00714	0.0146

OLS regressions, robust standard errors in parentheses. Base groups: Age 20–24, unskilled. Dubai Fateh Spot Oil price is the price per barrel for light sour crude oil extracted from Dubai, scaled to an index such that the price on May 1, 2008 equals 100. Thus all coefficients can be interpreted as a % difference in the instrument with respect to its May 1, 2008 value. "Rural" means a household located outside one of the 27 districts in the universe found within major metropolitan areas.

Table 4: Applicant wages and employment

	Mean	β_{OLS}	s.e.	$\beta_{\text{IV-2SLS}}$	s.e.	F_{MP}	$\beta_{\text{IV-DEV}}$	$(s.e.)$	N
Treatment: *Applicant is now in UAE*									
ln wage	8.963	0.946	(0.0394)	1.381	(0.501)	12.13	1.337	(0.463)	1551
Employed?	0.875	0.188	(0.0106)	0.253	(0.178)	17.71	0.247	(0.172)	2703
Treatment: *Applicant has ever been in UAE*									
ln wage	8.963	0.558	(0.0445)	1.429	(0.612)	9.839	1.121	(0.372)	1551
Employed?	0.875	0.107	(0.0127)	0.294	(0.219)	10.89	0.246	(0.153)	2703

Sample is job applicants only. 'Mean' is the mean value of the outcome in the survey sample. Wages in Indian rupees (at exchange rate) per month defined such than an unemployed person has zero wages. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with "in UAE" instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3. Wages do not include earnings from home-based family farm/business.

Table 5: Individual-level work and migration for adults other than the applicant

	Mean	β_{OLS}	s.e.	$\beta_{\text{IV-2SLS}}$	s.e.	F_{MP}	$\beta_{\text{IV-DEV}}$	$(s.e.)$	N
Treatment: *Applicant from household is now in UAE*									
Employed?	0.294	0.000269	(0.0111)	0.0455	(0.123)	69.73	0.0763	(0.157)	8525
Any wages?	0.232	0.0100	(0.0103)	−0.113	(0.114)	69.73	−0.103	(0.146)	8525
ln wage	8.359	0.0346	(0.0516)	0.250	(0.420)	28.16	0.161	(0.399)	1979
In UAE now?	0.0163	0.00599	(0.00351)	0.0581	(0.0350)	69.73	0.0659	(0.0453)	8525
Overseas now?	0.0269	−0.00154	(0.00421)	0.0651	(0.0445)	69.73	0.0730	(0.0579)	8525
Treatment: *Applicant from household has ever been in UAE*									
Employed?	0.294	−0.0364	(0.0106)	0.0590	(0.159)	37.21	0.0529	(0.144)	8525
Any wages?	0.232	−0.0134	(0.00972)	−0.146	(0.148)	37.21	−0.134	(0.134)	8525
ln wage	8.359	0.00346	(0.0492)	0.400	(0.684)	9.979	0.269	(0.453)	1979
In UAE now?	0.0163	−0.00303	(0.00332)	0.0753	(0.0465)	37.21	0.0679	(0.0420)	8525
Overseas now?	0.0269	−0.0151	(0.00416)	0.0844	(0.0591)	37.21	0.0756	(0.0537)	8525

Sample is working-age individuals in the applicants' households other than the applicant himself. 'Mean' is the mean value of the outcome in the survey sample. Wages in Indian rupees (at exchange rate) per month defined such than an unemployed person has zero wages. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with "in UAE" instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3. Wages do not include earnings from home-based family farm/business.

Table 6: Household income and expenditure

	Mean	β_{OLS}	s.e.	$\beta_{IV\text{-}2SLS}$	s.e.	F_{MP}	$\beta_{IV\text{-}DEV}$	$(s.e.)$	N
Treatment: *Applicant from household is now in UAE*									
Household size	5.264	−0.866	(0.125)	−3.175	(1.448)	18.15	−3.445	(1.482)	2713
ln income/cap.	7.420	0.177	(0.0450)	−0.814	(0.596)	16.79	−0.858	(0.581)	2471
Remittances?	0.344	0.605	(0.0177)	0.607	(0.212)	18.15	0.536	(0.208)	2713
ln remittances/cap.	6.965	0.0326	(0.0687)	−0.701	(0.883)	5.364	−0.777	(1.141)	934
ln total expenses/cap.	7.042	0.217	(0.0337)	0.549	(0.409)	17.36	0.473	(0.348)	2236
…food	6.315	0.179	(0.0285)	0.249	(0.358)	18.30	0.322	(0.345)	2691
…quality of life	5.466	0.0244	(0.0637)	0.878	(0.687)	18.11	1.298	(0.723)	2700
…medical	4.486	0.245	(0.0571)	1.147	(0.712)	18.32	1.023	(0.657)	2517
…education	4.294	0.241	(0.0693)	0.838	(0.864)	13.12	0.500	(0.773)	1836
…durable goods	3.462	0.122	(0.0922)	−1.360	(1.406)	7.932	−2.318	(2.088)	1526
Treatment: *Applicant from household has ever been in UAE*									
Household size	5.264	−0.339	(0.101)	−3.616	(1.825)	11.54	−2.739	(1.281)	2713
ln income/cap.	7.420	0.0320	(0.0419)	−1.055	(0.792)	8.497	−0.705	(0.511)	2471
Remittances?	0.344	0.216	(0.0196)	0.692	(0.320)	11.54	0.561	(0.221)	2713
ln remittances/cap.	6.965	0.0216	(0.0692)	−0.679	(0.851)	5.781	−0.708	(1.087)	934
ln total expenses/cap.	7.042	0.185	(0.0301)	0.603	(0.458)	11.40	0.455	(0.286)	2236
…food	6.315	0.151	(0.0263)	0.272	(0.391)	12.76	0.233	(0.282)	2691
…quality of life	5.466	−0.00831	(0.0548)	0.980	(0.787)	12.00	0.733	(0.577)	2700
…medical	4.486	0.131	(0.0522)	1.288	(0.839)	11.85	0.934	(0.555)	2517
…education	4.294	0.209	(0.0659)	0.960	(1.005)	8.247	0.749	(0.726)	1836
…durable goods	3.462	0.124	(0.0840)	−1.394	(1.473)	5.831	−1.145	(1.173)	1526

Sample is job applicants' households. 'Household size' does not include household members currently abroad, and this size is used to calculate all 'per capita' values. Income, remittances, and expenditure are in Indian rupees per month, per capita. 'Quality of life' expenditures include fuel, electricity, personal care, entertainment, personal services, transportation, and rent. 'Mean' is the mean value of the outcome in the survey sample. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with "in UAE" instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3. Wages do not include earnings from home-based family farm/business.

Table 7: Household business activity

	Mean	β_{OLS}	s.e.	$\beta_{\text{IV-2SLS}}$	s.e.	F_{MP}	$\beta_{\text{IV-DEV}}$	(*s.e.*)	N
Treatment: *Applicant from household is now in UAE*									
Any business profit?	0.0878	−0.0238	(0.0101)	0.176	(0.141)	18.15	0.147	(0.131)	2713
Business revenue	359.1	−277.1	(78.43)	11.10	(887.9)	18.15	−122.1	(1095.4)	2713
Business profit	182.2	−172.2	(53.13)	22.68	(646.2)	18.15	−79.70	(740.2)	2713
Treatment: *Applicant from household has ever been in UAE*									
Any business profit?	0.0878	0.000757	(0.00946)	0.201	(0.162)	11.54	0.145	(0.111)	2713
Business revenue	359.1	−27.17	(71.63)	12.64	(1011.1)	11.54	−34.40	(934.8)	2713
Business profit	182.2	−6.506	(51.67)	25.84	(735.5)	11.54	−8.947	(631.6)	2713

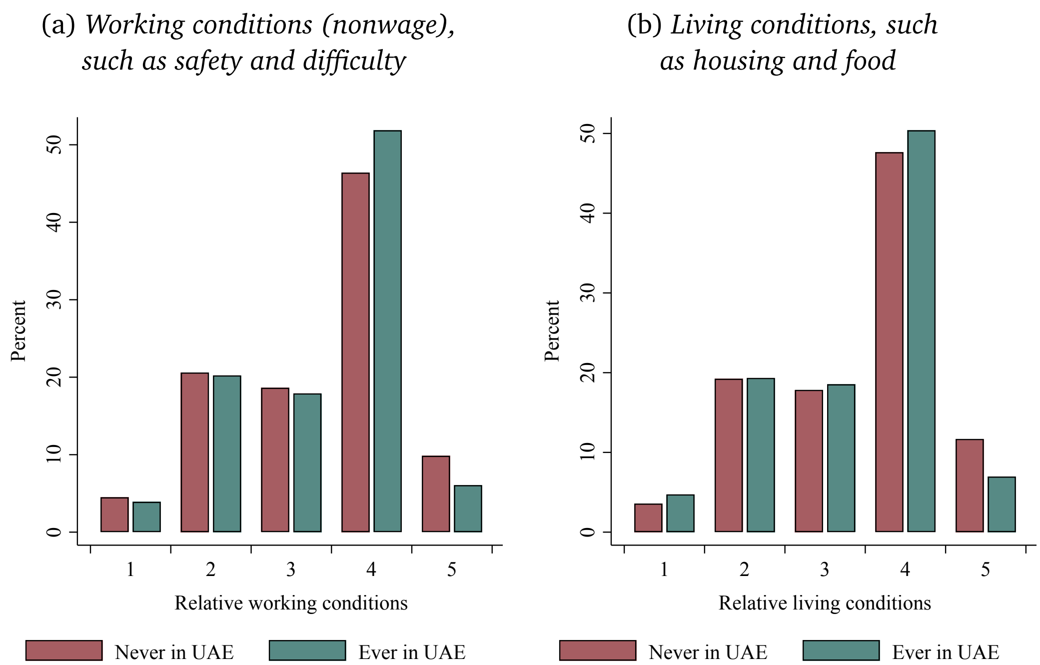
Sample is job applicants' households. Revenue and profits are in Indian rupees per month. 'Mean' is the mean value of the outcome in the survey sample. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with "in UAE" instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3. Wages do not include earnings from home-based family farm/business.

Table 8: Household assets

	Mean	β_{OLS}	s.e.	$\beta_{\text{IV-2SLS}}$	s.e.	F_{MP}	$\beta_{\text{IV-DEV}}$	$(s.e.)$	N
Treatment: *Applicant from household is now in UAE*									
Television	0.774	−0.0218	(0.0156)	−0.110	(0.168)	18.15	−0.161	(0.173)	2713
Sewing machine	0.278	−0.0386	(0.0197)	−0.179	(0.242)	18.15	−0.171	(0.235)	2713
Refrigerator	0.418	0.0182	(0.0164)	0.458	(0.245)	18.15	0.358	(0.225)	2713
Motorcycle	0.484	−0.0285	(0.0202)	−0.315	(0.256)	18.15	−0.316	(0.249)	2713
Treatment: *Applicant from household has ever been in UAE*									
Television	0.774	−0.0110	(0.0129)	−0.125	(0.192)	11.54	−0.0960	(0.147)	2713
Sewing machine	0.278	−0.0379	(0.0180)	−0.203	(0.278)	11.54	−0.155	(0.200)	2713
Refrigerator	0.418	0.0483	(0.0159)	0.521	(0.290)	11.54	0.388	(0.195)	2713
Motorcycle	0.484	0.0288	(0.0183)	−0.359	(0.305)	11.54	−0.255	(0.214)	2713

Sample is job applicants' households. 'Mean' is the mean value of the outcome in the survey sample. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with "in UAE" instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3. Wages do not include earnings from home-based family farm/business.

Figure 4: Household opinions of relative UAE/India nonwage amenities, by direct exposure to UAE guest work



'Never in UAE' means that the responding household does not report any member has ever having worked in the UAE; classified as 'ever in UAE' otherwise. In each case, 1 = 'much worse than here' (i.e. much worse in the UAE than in India), 2 = 'worse than here', 3 = 'similar to here', 4 = 'better than here', and 5 = 'much better than here'. If any man in the household was *currently* in the UAE at the time of the interview in 2011, in panel (a) the respondent was asked to "*think about his working conditions in the UAE, apart from his earnings. I mean working conditions such as safety, enjoyment of the work, difficulty of the work. Do you think that his working conditions are worse or better there than they would be here?*" and in panel (b) was asked to "*think about his living conditions in the UAE—such as housing and food. Do you think that his living conditions are worse or better there than they would be here?*" If no man in the household was *currently* in the UAE at the time of the interview, the respondent in panel (a) was asked hypothetically to "*suppose, for a moment, that one man from this household had the opportunity to work for a few years in UAE. Apart from his earnings: Now think about what his working conditions in the UAE would be like, I mean working conditions such as safety, enjoyment / difficulty of the work. What do you think about his working conditions in UAE as compared to the working conditions in INDIA?*" And in panel (b), the respondent was asked hypothetically to "*think about what his living conditions in the UAE—such as housing and food. What do you think about his living conditions in UAE as compared to the living conditions in INDIA?*"

Table 9: Effects on household-level impressions of relative UAE working and living conditions

	Mean	β_{OLS}	s.e.	$\beta_{\text{IV-2SLS}}$	s.e.	F_{MP}	$\beta_{\text{IV-DEV}}$	$(s.e.)$	N
Treatment: *Any man from household is now in UAE*									
ln wage (actual or guess)	9.780	−0.217	(0.0304)	0.466	(0.405)	15.88	0.226	(0.351)	2259
Working conditions (actual or guess)	3.310	−0.0644	(0.0479)	1.197	(0.669)	15.72	0.842	(0.583)	2254
Living conditions (actual or guess)	3.364	−0.0816	(0.0480)	0.263	(0.590)	15.46	0.0900	(0.552)	2222
Treatment: *Any man from household has ever been in UAE*									
ln wage (actual or guess)	9.780	−0.106	(0.0268)	0.480	(0.418)	10.78	0.298	(0.290)	2259
Working conditions (actual or guess)	3.310	−0.0454	(0.0420)	1.302	(0.762)	9.931	0.909	(0.504)	2254
Living conditions (actual or guess)	3.364	−0.0704	(0.0427)	0.282	(0.633)	10.17	0.190	(0.468)	2222

Sample is job applicants' households. 'Mean' is the mean value of the outcome in the survey sample. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with "in UAE" instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3. For the ratings of relative working and living conditions, 1 = 'much worse than here' (i.e. much worse in the UAE than in India), 2 = 'worse than here', 3 = 'similar to here', 4 = 'better than here', and 5 = 'much better than here'. If any man in the household was *currently* in the UAE at the time of the interview in 2011, in panel (a) the respondent was asked to "*think about his working conditions in the UAE, apart from his earnings. I mean working conditions such as safety, enjoyment of the work, difficulty of the work. Do you think that his working conditions are worse or better there than they would be here?*" and in panel (b) was asked to "*think about his living conditions in the UAE—such as housing and food. Do you think that his living conditions are worse or better there than they would be here?*" If no man in the household was *currently* in the UAE at the time of the interview, the respondent in panel (a) was asked hypothetically to "*suppose, for a moment, that one man from this household had the opportunity to work for a few years in UAE. Apart from his earnings: Now think about what his working conditions in the UAE would be like, I mean working conditions such as safety, enjoyment / difficulty of the work. What do you think about his working conditions in UAE as compared to the working conditions in INDIA?*" And in panel (b), the respondent was asked hypothetically to "*think about what his living conditions in the UAE—such as housing and food. What do you think about his living conditions in UAE as compared to the living conditions in INDIA?*"

Table 10: Effects on household borrowing and debt

	Mean	β_{OLS}	s.e.	$\beta_{\text{IV-2SLS}}$	s.e.	F_{MP}	$\beta_{\text{IV-DEV}}$	(*s.e.*)	N
Treatment: *Any man from household is now in UAE*									
Borrowed in last 3 years?	0.578	0.0825	(0.0215)	0.148	(0.256)	18.64	0.107	(0.0235)	2722
...for migration?	0.256	0.180	(0.0211)	0.0791	(0.219)	18.64	0.0883	(0.0208)	2722
Total borrowed	73532.5	16772.5	(8891.8)	117154.8	(140481.1)	18.52	18659.7	(12593.6)	2624
Any debt now?	0.933	−0.0112	(0.0122)	−0.203	(0.135)	19.12	0.0146	(0.0131)	2569
Amount of current debt	39817.5	2773.9	(5253.0)	−31996.8	(113775.7)	19.12	1107.0	(10128.9)	2569
Treatment: *Any man from household has ever been in UAE*									
Borrowed in last 3 years?	0.578	0.0655	(0.0195)	0.173	(0.301)	11.25	0.108	(0.0235)	2722
...for migration?	0.256	0.140	(0.0176)	0.0925	(0.256)	11.25	0.0930	(0.0208)	2722
Total borrowed	73532.5	22189.1	(10324.1)	131463.9	(158589.3)	12.08	18278.5	(12575.2)	2624
Any debt now?	0.933	−0.0145	(0.0102)	−0.228	(0.155)	12.50	0.0150	(0.0130)	2569
Amount of current debt	39817.5	5511.8	(6900.2)	−35811.8	(127575.2)	12.50	984.2	(10121.5)	2569

Sample is job applicants' households. Borrowing and debt measured in Indian rupees. 'Mean' is the mean value of the outcome in the survey sample. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with "in UAE" instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3.

Online Appendix

“Household effects of temporary low-skill work visas:
Evidence from the India-Gulf corridor”

A1 Descriptive statistics

Table A1 presents descriptive statistics for the variables used in the regressions in the main text.

A2 Global stock of legal low-skill temporary workers

Sources for country totals of legal temporary workers are presented in Appendix Table A2. Data for the labor force size of Argentina (19.1m), Poland (18.5m), and the 31 other countries with the largest labor forces in 2013 are from the International Labor Organization, as reported by the World Bank *World Development Indicators* (SL.TLF.TOTL.IN, accessed Feb. 1, 2015).

A3 Nationally-representative data

A3.1 India National Sample Survey (NSS) 2008

Education levels are defined according to cases of *l4educationgen*: “Illiterate” = 1; “Read & Write” = 2–6; “Primary” = 7; “Preparatory” = 8; “Secondary” = 10; “Above Secondary” = 11–12; “University” = 13; “Above University” = 14.

‘Relevant’ occupations are defined for the India NSS data, according to India’s National Classification of Occupations 2004, as: 712 “Building Frame and Related Trades Workers”; 713 “Building Finishers and Related Trades Workers”; 714 “Painters, Building Structure Cleaners and Related Trades Workers”; 721 “Metal Moulders, Welders, Sheet Metal Workers, Structural Metal Preparers and Related Trades Workers”; 724 “Electrical and Electronic Equipment Mechanics and Fitters”; 742 “Wood Treaters, Cabinet Makers and Related Trades Workers”; 821 “Metal and Mineral Products Machine Operators”; 831 “Locomotive Engine Drivers and Related Workers”; 832 “Motor Vehicle Drivers”; 931 “Mining and Construction Labourers”; 516 “Protective Services Workers”.

Because the India NSS uses sampling (probability) weights and the UAE LFS uses relative weights, the NSS weights are adjusted to relative weights when the datasets are stacked together. That is, the NSS sampling weights are multiplied by the ratio of sample size to the sum of the sampling weights—converting them to relative weights.

A3.2 UAE Labor Force Survey (LFS) 2008

Education levels are defined according to cases of *Q108_C*: “Illiterate” = 1; “Read & Write” = 2; “Primary” = 3; “Preparatory” = 4; “Secondary” = 5; “Above Secondary” = 6; “University” = 7; “Above University” = 8–10. Wage is calculated as total of wage in cash and in kind. The wage reported in dirhams is converted to rupees at the exchange rate of ₹10.99/dirham, which was the average exchange rate during the period that the NSS data was collected (July 2007–June 2008). Nationals of countries other than UAE and India are dropped.

Appendix Table A1: Descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Individual applicants					
In UAE now?	0.297	0.457	0	1	2715
In UAE ever?	0.488	0.5	0	1	2715
ln wage	8.963	0.935	4.828	12.766	1557
Employed?	0.875	0.331	0	1	2715
Age	29.015	5.765	20	65	2712
Skilled?	0.4	0.49	0	1	2715
Semiskilled?	0.487	0.5	0	1	2715
Rural?	0.67	0.47	0	1	2715
Muslim?	0.302	0.459	0	1	2715
Individual non-applicant adults					
Employed?	0.294	0.455	0	1	8552
Any wage inc.?	0.232	0.422	0	1	8552
ln wage	8.359	1.051	4.423	11.562	1986
In UAE now?	0.016	0.126	0	1	8552
Overseas now?	0.027	0.162	0	1	8552
Households					
Household size (in India)	5.264	2.989	1	34	2723
ln income/cap.	7.42	1.128	1.427	11.051	2480
Any remittances?	0.344	0.475	0	1	2723
ln remittances/cap.	6.965	1.215	2.408	10.714	936
ln total expenses/cap.	7.042	0.772	3.954	9.898	2245
...food	6.315	0.736	3.624	9.17	2701
...quality of life	5.466	1.291	−3.232	8.987	2710
...medical	4.486	1.243	0.174	8.74	2526
...education	4.294	1.4	−0.875	9.028	1844
...durable goods	3.462	1.68	−1.435	8.805	1532
Any business profit?	0.088	0.283	0	1	2723
Business revenue	359.062	2118.252	0	51666.668	2723
Business profit	182.187	1411.569	−5000	45000	2723
Own television	0.774	0.418	0	1	2723
...sewing machine	0.278	0.448	0	1	2723
...refrigerator	0.418	0.493	0	1	2723
...motorcycle	0.484	0.5	0	1	2723
ln wage (guess or actual)	9.779	0.686	6.397	12.899	2269
working conditions (guess or actual)	3.31	1.022	1	5	2263
living conditions (guess or actual)	3.364	1.035	1	5	2231

Appendix Table A2: Lower bound on global stock of legal low-skill temporary workers

Countries	Stock	Year	Includes	Source
GCC	13,600,000	2013	'Low-skill' foreign nationals	A, pp. 9, 11.
Malaysia	2,100,000	2013	'Visit Pass (Temporary Employment)'	B, p. 128.
Korea	547,300	2011	Low-skill work permit holders	C, p. 268
Singapore	533,400	2013	'Construction' & 'Domestic Worker'	D
Russian Federation	400,000	2011	1.2m work-permit holders, 1/3 low-skill	C, p. 290
Germany	168,000	2011	Seasonal only	C, p. 255
United States	131,792	2013	H-2A and H-2B	E
Canada	84,630	2013	Low-skill workers present on Dec. 1	F, p. 4:
Israel	32,000	2012	Agriculture and construction only	C, p. 262.
United Kingdom	16,300	2011	Seasonal only	C, p. 305
Italy	15,200	2011	Seasonal only	C, p. 265
Finland	12,000	2011	Seasonal only	C, p. 251
France	8,000	2011	Seasonal only	C, p. 252
New Zealand	7,456	2013	Seasonal agricultural workers	G
Sweden	3,800	2011	Seasonal only	C, p. 299
Norway	2,500	2011	Seasonal only	C, p. 283
Spain	2,200	2011	Seasonal only	C, p. 297
Australia	2,000	2013	Seasonal agricultural workers	H
Total lower bound	17,666,578			

'Stock' means the number of workers who are on legal low-skill temporary work visas during any portion of a year, whether those workers begin and end the year at the destination or arrive at and/or depart from the destination during that year; these numbers are not flows of new migrants. 'GCC' is Gulf Cooperation Council. Sources: **A:** IMF, 2013, *Labor Market Reforms to Boost Employment and Productivity in the GCC* [Population of GCC, and foreign nationals as % of population from Table 1 p. 11. Low skill over 80% from Fig. 6 page 9. Thus $0.8 \times 0.384 \times (1.2 + 3.8 + 3.1 + 1.8 + 29 + 5.5) \times 10^6 = 13.64\text{m}$]. **B:** Malaysia Ministry of Finance, 2014, *Economic Report 2014/2015*. **C:** OECD *International Migration Outlook 2013*. **D:** Singapore Ministry of Manpower, 2014, "Foreign Workforce Numbers", accessed Nov. 6, 2014. **E:** US State Dept, 2014, *Report of the Visa Office 2013*. **F:** ESDC 2014, Overhauling the Temporary Foreign Worker Program. **G:** NZ Ministery of Business, Innovation, and Employment, 2014, RSE Workers Arrival into New Zealand—RSE Financial Year 2012/2013. **H:** Henry Sherrell 2014, "An update on the Australian Seasonal Worker Program".

‘Relevant’ occupations are defined, for the UAE LFS data, as: 7136 “Workers of electrical wiring in buildings”; 9313 “Building construction workers”; 3113 “Assistant electrical engineer”; 7221 “Blacksmiths and workers hammers and pistons”; 2145 “Mechanical Engineer”; 2142 “Civil Engineer”; 7122 “Construction workers with bricks and stones”; 7123 “Workers Pour Concrete”; 8333 “Operators of cranes and equipment to transport materials”; 7242 “Electrical repair and service equipment and electronic equipment”; 3112 “Assistant Civil Engineer”; 2143 “Electrical Engineer”; 7124 “Njaro construction and fixtures”; 7135 “Plumbers”; 7143 “Workers installing tiles and wooden flooring Mbtaiw”; 7121 “Builders traditional materials”; 7212 “Welders and flame-cutting”; 7245 “Workers install and repair electrical lines and cables”; 1223 “Business managers and production activity in construction”; 9312 “Construction workers and maintenance of roads, dams, etc.”; 7144 “Building structure cleaners”; 7125 “Other makers of building structures”; 7133 “Workers put insulation”; 9331 “Drivers and vehicles driven by hand or towed Softswitch”; 9141 “Building Service Workers”; 7136 “Workers of electrical wiring in buildings”; 9313 “Building construction workers”; 7122 “Construction workers with bricks and stones”; 7123 “Workers Pour Concrete”; 7124 “Njaro construction and fixtures”; 7135 “Plumbers”; 7121 “Builders traditional materials”; 7245 “Workers install and repair electrical lines and cables”; 1223 “Business managers and production activity in construction”; 9312 “Construction workers and maintenance of roads, dams, etc.”; 7144 “Building structure cleaners”; 7125 “Other makers of building structures”; 7133 “Workers put insulation”; 3115 “Assistant Mechanical Engineer”; 7239 “Mechanical installation and repair of machinery”; 9141 “Building Service Workers”; 9132 “Cleaners in offices, hotels and institutions”; 8322 “Drivers of small cars, pick-ups”.

A4 Nonresponse bias

Figure A5 shows a moving average of the probability that an applicant on each date had obtained a UAE labor card by November 2011 (which requires physical presence in the UAE), in the sampling universe, broken down by survey attempt outcome. Similar patterns of migration in the sampling universe are observed for the households that were successfully surveyed, the households whose job application did not provide enough information to locate their residence (‘bad address’), and households that were successfully located but did not yield a completed survey—either because no one could be found at the residence, the applicant’s family was found at the residence but refused to participate in the survey, or the applicant’s family had moved away from the residence.

A5 Children

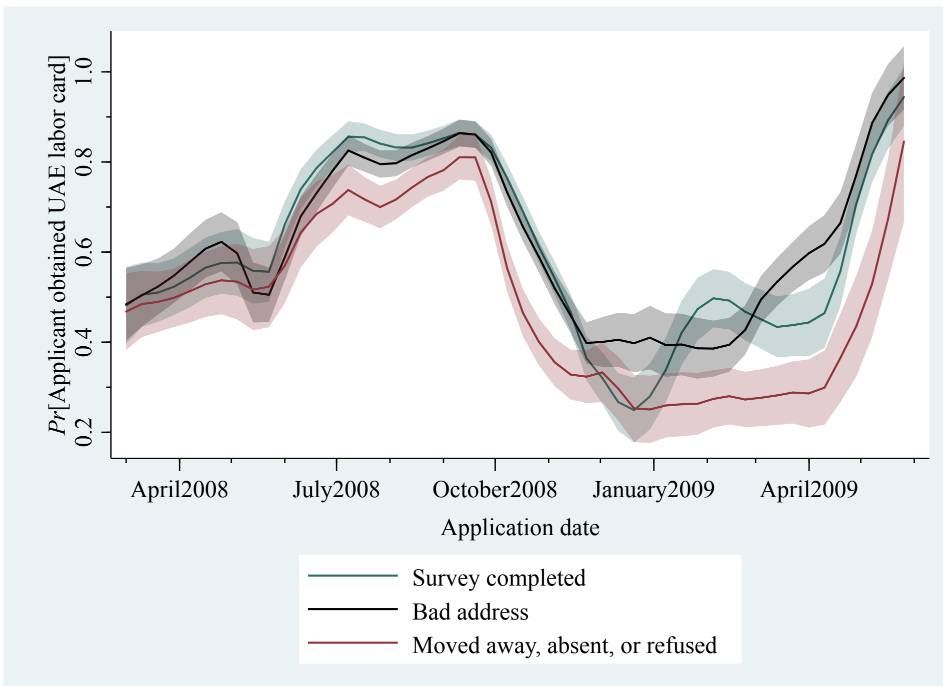
Table A3 shows estimated effects on individual school-age children of the job applicant. The outcomes tested are labor-force participation, school attendance, and indicators of performance (awards) and parental involvement in children’s schooling. The low Montiel-Pflueger F-statistic in all regressions suggests that all IV coefficients in the table are subject to severe bias from weak instrumentation.

Appendix Table A3: Effects on school-age children of the job applicant—uninformative due to weak instrumentation

	Mean	β_{OLS}	s.e.	$\beta_{IV\text{-}2SLS}$	s.e.	F_{MP}	$\beta_{IV\text{-}DEV}$	$(s.e.)$	N
Treatment: *Applicant from household is now in UAE*									
Employed?	0.0133	−0.00175	(0.00856)	0.0436	(0.169)	2.292	0.000710	(0.110)	1124
Any wage income?	0.0124	−0.000903	(0.00851)	0.0939	(0.169)	2.292	0.0254	(0.107)	1124
In school?	0.904	−0.00658	(0.0231)	−0.357	(0.548)	2.292	−0.125	(0.293)	1124
. . . private school?	0.586	0.158	(0.0347)	−0.417	(0.853)	2.529	−0.179	(0.460)	1017
Days missed	1.956	−0.156	(0.288)	−2.335	(7.220)	2.420	−0.0624	(3.856)	1016
Award?	0.166	0.0843	(0.0299)	0.278	(0.642)	2.529	0.207	(0.353)	1017
Guidance?	0.540	0.00608	(0.0380)	−0.371	(0.860)	2.529	−0.0674	(0.462)	1017
Discuss teacher?	0.868	0.167	(0.142)	−2.011	(3.653)	2.948	−0.267	(2.876)	930
Treatment: *Applicant from household has ever been in UAE*									
Employed?	0.0133	−0.00222	(0.00670)	0.0539	(0.214)	0.923	0.0181	(0.0955)	1124
Any wage income?	0.0124	−0.000778	(0.00655)	0.116	(0.230)	0.923	0.0434	(0.0934)	1124
In school?	0.904	0.0194	(0.0178)	−0.442	(0.781)	0.923	−0.162	(0.260)	1124
. . . private school?	0.586	0.0453	(0.0310)	−0.596	(1.342)	0.740	−0.204	(0.436)	1017
Days missed	1.956	−0.0120	(0.240)	−3.468	(11.51)	0.655	−1.199	(3.718)	1016
Award?	0.166	0.0115	(0.0246)	0.397	(0.987)	0.740	0.139	(0.337)	1017
Guidance?	0.540	0.0841	(0.0321)	−0.529	(1.369)	0.740	−0.141	(0.445)	1017
Discuss teacher?	0.868	0.526	(0.228)	−3.607	(7.984)	0.566	−1.077	(2.954)	930

Sample is school-age children of the job applicant when the job applicant is the head of the household. ‘Days missed’ is the answer to the question, “In the last 30 days, how many days has (NAME) missed school when it was in session?”. ‘Award’ is 1 if the answer is “yes” to “In the last one month, did (NAME) get an award or prize in the school?” and zero otherwise. ‘Guidance’ is 1 if the answer is “yes” to “Does anyone in the household help (NAME) in studies/teaching/providing guidance?” and zero otherwise. ‘Discuss teacher’ is 1 if the answer is “yes” to “During the last one year, how many times did someone from the family discuss (NAME)’s school work with the teacher?” and zero otherwise. ‘Mean’ is the mean value of the outcome in the survey sample. OLS is ordinary least squares with robust standard errors. IV-2SLS is two-stage least squares, with “in UAE” instrumented by the Dubai Fateh oil price index on the day of job application, and F_{MP} is the Montiel-Pflueger (2013) F-statistic testing the null of weak instrumentation. IV-DEV is the dummy endogenous variable IV model. All regressions include a constant and controls for the predetermined applicant traits given in Table 3. Wages do not include earnings from home-based family farm/business.

Figure A5: Sampling universe: UAE administrative records on probability of applicant arrival, by survey attempt outcome



Shaded bands show 95% confidence intervals on local regression, Epanechnikov kernel, bandwidth 15 days, degree 0.