**Upward or Downward:**

**Occupational Mobility and Return Migration**\*

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**Abstract**

This paper examines whether temporary international migration enables returnees to climb the occupational ladder. Using data from Egypt, we examine the occupational mobility of returnees relative to non-migrants of the same birth cohort. We rely on an instrumental variable approach to control for the endogeneity of the temporary migration decision. We find evidence that return migration increases the probability of upward occupational mobility and leads to larger effects among highly educated returnees. Our results are robust to using a Difference-in-Differences matching technique that controls for unobserved heterogeneity between non-migrants and returnees. Our findings underscore that temporary overseas work experience can alleviate potential brain drain concerns through the human capital enhancement of return migrants.

Keywords: return migration, occupational mobility, Egypt, Middle East and North Africa.

JEL codes: F22, J62.

1. **Introduction**

For many developing countries, the emigration of high-skilled workers is a source of concern. The loss of highly productive workers—brain drain—is seen as a negative consequence of international emigration. However, international migration could lead to brain gain as well, when the possibility of emigration increases the expected return to human capital and leads to more investment in education by both migrants and remaining workers (Mayr and Peri, 2009). From a macro perspective, Beine, Docquier and Rapoport (2008) and Beine, Docquier and Oden-Defoort (2011) find a positive effect of skilled migration prospects on gross human capital formation, particularly in low-income countries. Moreover, using individual level data, Batista, Lacuesta and Vincente (2012) find a sizable positive effect of the own future probability of emigration on educational attainment in Cape Verde, a country with high emigration rates among the most educated.

Return migration is another channel through which high-skilled migration can result in a brain gain: when migrants return after having accumulated skills overseas, enhancing the average human capital of the origin country.[[3]](#footnote-3) Individuals might migrate temporarily as part of an optimal strategy to maximize lifetime utility. Due to credit constraints, individuals migrate, for a period of time, where wages are higher so that they can accumulate overseas savings. Alternatively, they migrate temporarily to acquire skills that are highly rewarded in the origin country (Dustmann, Fadlon and Weiss, 2011). Within this framework, temporary migration provides an opportunity for workers to acquire physical capital (savings) and human capital (new skills and knowledge). Return of migrants with their financial and human capital investments can be a potential source of economic growth for the origin country, through increased productivity and knowledge diffusion (Choudhury, 2016; Djajić, 2014; Dos Santos and Postel-Vinay, 2003 Dustmann and Gorlach, 2016; Sun, 2013).[[4]](#footnote-4) Indeed, whether migrants acquire human capital while overseas is an important question for the economic development of sending developing countries, since the public debate tends to underscore the negative impact of high-skilled emigration, resulting in a brain drain.

Return migration is still a relatively understudied aspect of international migration, despite its importance. Largely the literature on the impact of international migration has focused on the remittances and savings of migrants and, to a lesser extent, on the effect of return migration on human capital accumulation, i.e. on the brain gain channel. The latter literature has focused on the wage premium earned by return migrants compared to non-migrants.[[5]](#footnote-5) The evidence suggests that there is a positive wage premium associated with overseas work migration for returnees in developing countries (Lacuesta, 2010; Reinhold and Thom, 2013; Wahba, 2015). However, these studies only observe wages at one point in time and typically speculate that the wage premium (of returnees compared to non-migrants) is due to overseas human capital accumulation but cannot control for pre-migration wages.

Another unexplored measure of the acquisition of human capital of temporary migrants is their skill upgrading or occupational mobility. The existing literature on the impact of return on upward mobility is very sparse.[[6]](#footnote-6) Carletto and Kilic (2011) estimate the impact of international migration experience on the occupational mobility of returnees compared to stayers in Albania and find that past migration experience increases the probability of upward occupational mobility. Relying on an instrumental variable approach to control for the endogeneity of international migration and return, they use foreign language knowledge of household members before migration and the number of young children at the time of return, as predictors of past migration and return decisions. Both, however, are potentially choice variables that might violate the exclusion restriction. On the other hand, using the online job search portal of Estonia, Eamets, Jaakson, Masso and Mõtsmees (2014) investigate the effect of temporary migration experience on upward occupational mobility, using data based on resumes submitted to an online job search portal. As instruments, they use cohabitation and number of children, which are choice variables. They find that temporary migration experience does not exhibit any significant effect on upward occupational mobility, but this could be due to the very selective nature of those using an online job search portal and the information they report about their previous occupations online.

Our paper also contributes to the interdisciplinary development literature on return migration. Olesen (2002) points out the importance of migration as a key parameter for development policies and discusses possibilities of using return migration as a policy instrument to achieve brain gain. Black and King (2004) also highlight the role of migrants from Senegal whose temporary return to origin communities enhances the potential to promote development, as they strengthen the bond between migrants and home communities. Meanwhile, Ammassari (2004) focuses on two other countries in West Africa, Ghana and Côte d’Ivoire, and examines the re-integration of highly educated returnees, highlighting their role as catalysts for development of the origin countries, through increased productive investment and entrepreneurship. Moreover, Thomas (2008) provides evidence from Uganda, suggesting that skilled return migrants have a greater likelihood of being employed upon return compared to non-migrants.

Return migration can also have a positive impact on job-creating activities, as suggested by Piracha and Vadean (2010) and Démurger and Xu (2011), who provide evidence on increased engagement in entrepreneurial activities among return migrants in Albania and rural China, respectively. Meanwhile, Marchetta (2012) finds that returnees’ migration experiences significantly improve the chances of survival of entrepreneurial activities. Cassarino (2004, 2008) stresses the role of “return preparedness” in achieving successful re-integration after return, emphasizing the conditions under which some returnees appear as actors of change and have positive effects on the development of their home communities. Cassarino argues that optimal outcomes hinge upon the capacity of return migrants to acquire social, financial, and human capital while abroad. According to this framework, returnees who were able to gather all the tangible and intangible resources necessary to secure their return are more likely to witness a successful re-insertion at home.

Our paper contributes to the literature on return migration in at least three ways. First, the impact of overseas migration on occupational mobility after return is ambiguous. On one hand, temporary migrants might acquire additional human capital due to their work experience abroad. The human capital accumulated abroad might hence help temporary migrants find occupations higher in the skill and remuneration ladder upon return. On the other hand, it might be the case that temporary migration experience is motivated by the shortage of unskilled labor in destination countries and subsequently the positive effects of temporary migration on human capital and occupational upgrading might not hold.[[7]](#footnote-7) Secondly, when comparing the wage premium of returnees, relative to non-migrants, previous studies do not disentangle the effect of occupational upgrading as they tend to control for job characteristics (including occupations). In principle, if returnees experience wage premiums upon return, this could be due to two types of mobility: (i) horizontal mobility (same occupation, but different jobs) or (ii) vertical occupational mobility (moving to a higher ranked occupation). In a sense, if return migration allows home countries to upskill and move the working population up the skill ladder, this would allow structural change and economic growth. Indeed, sectorial and occupational mobility is a pillar of economic development. Yet, little is known about the impact of temporary migration on occupational mobility, which is central to the economic development of the country of origin. Finally, whether temporary emigration and overseas work experience enhance human capital accumulation is an important policy question. An understudied issue is thus whether return migration can promote the economic development of sending countries and compensate for the loss of human capital through occupational mobility.

Qualitative evidence from a detailed survey on the impact of migration on skill development in Egypt, conducted by the European Training Foundation (ETF) in 2006-2007, points to the potential impact of overseas work experience on the occupational mobility of returnees. The ETF survey interviewed non-migrants as well as return migrants.[[8]](#footnote-8) About 66% of returnees reported that their experiences abroad helped them find better work since their return to Egypt. Interestingly, 27% reported that the skills learned overseas where the most helpful, while 37% mentioned that the migration experience in general (and exposure to new ways in particular) helped them. Also 83% of returnees believed they were better off than before migration (71% among the less educated and 86% among highly educated returnees). This descriptive evidence indeed suggests that returnees can benefit from overseas skills and provides additional motivation for our empirical analysis.

This paper provides evidence on the impact of temporary migration experience on the human capital accumulation of returnees. It examines the occupational mobility of return migrants vis-à-vis working-age individuals who have never migrated, controlling for the potential endogeneity of temporary migration. We rely on an instrumental variable approach, following Wahba and Zenou (2012) and Bertoli and Marchetta (2015). We use historical inflation-adjusted oil prices to obtain an exogenous source of variation in the probability of migration. Unlike previous studies, where wages or occupations are only observed at the time of survey, we are able to control for individuals’ first occupations and construct occupational mobility indicators based on the first and current occupations. We also rely on cohort analysis to control for birth cohort effects. Furthermore, we show that our results are robust to using a Difference-in-Differences matching technique that accounts for unobserved heterogeneity between the treatment and control groups and allows for a within comparison between each pair of matched stayer and returnee with similar first occupations.

We use data from the 2012 Egypt Labor Market Panel Survey (ELMPS). Egypt is a country with substantial temporary international migration. According to the ELMPS data, in 2012, almost 9 percent of men aged 15 to 59 were return migrants. We rely on birth cohort analysis and examine individuals’ occupational mobility between the first job and the job in 2010, thus before the January 2011 revolution, to ensure that our results can be generalized and are not affected by momentous events in the aftermath of the Arab Spring uprisings. Controlling for the endogeneity of temporary migration, we find that return migration increases the probability of upward occupational mobility. Our results are robust to using a Difference-in-Differences matching technique and also to using different birth cohorts. Our findings suggest that individuals drawn from the upper end of the educational distribution have a greater probability to climb the occupational ladder upon return. In line with the human capital accumulation literature, we find that the positive effect of return migration on occupational upgrading is larger the longer the duration of the migration experience. This suggests that return migration can indeed lead to a brain gain.

The rest of this paper is organized as follows. Section 2 provides a brief description of Egyptian migration and the data used in our analysis. Section 3 describes the empirical strategy. Section 4 presents the results. Section 5 provides robustness checks and discusses potential mechanisms. Section 6 concludes.

1. **Background on Egyptian migration and the data**
   1. **Egyptian migration**

Egyptian migration underwent distinct phases in the last four decades. Until 1971, Egyptian migration was limited, as it was subject to legal restrictions. The largest boost to outward migration flows occurred when the government lifted all restrictions on labor migration after the adoption of the 1971 constitution that legalized permanent and temporary emigration. One key factor contributing to the boost in outward migration flows was the 1973 war, following which oil revenues quadrupled. Gulf countries thereafter started implementing major development programs. Labor shortages in the Gulf triggered increased demand for foreign labor and, in response, massive emigration from Egypt. The majority of Egyptian migrants went to oil exporting Arab countries (the Gulf States, Libya and Iraq).

In the 1980s and in the 1990s, Asian workers started to gradually replace Arab workers; however, Egyptian migration to the Gulf countries did not cease but continued on a lower scale. By the mid 1990s, Saudi Arabia was the main destination country for Egyptian migrants, who represented the second largest migrant group, surpassed only by Indian nationals. At the same time, Egyptian workers also migrated to non-oil exporting Arab Countries (Jordan and Lebanon) to replace nationals of those countries who migrated to the Gulf. In the 2000s, Saudi Arabia remained a major destination country, while Libya hosted a quarter of Egyptian migrants. Iraq was no longer prominent and was replaced by Kuwait and the United Arab Emirates.

On the whole, Egyptian migration is characterized by its temporary nature, with mean migration duration of around five years according to the 2012 ELMPS data. It is also known to be male dominated, as young men migrate to achieve some financial goals and return to Egypt. Hence, Egypt is a country with a substantial number of returnees with overseas work experience, which provides us with a good case to study the impact of temporary overseas migration. A few papers have focused on the impact of temporary migration experience and return migration in Egypt, though none has investigated the role of return migration on occupational mobility.[[9]](#footnote-9)

Return migration represents an important fraction of all migration events. Recent estimates suggest that roughly one-quarter of all migration events are returns (Azose and Raftery, 2019). Indeed, the Gulf States, in particular, host a large proportion of working immigrants, and almost all are temporary migrants who require sponsorship and do not have citizenship rights. Therefore, understanding the impact of such temporary/return migration is crucial for countries of origin.

* 1. **Data**

The empirical analysis relies on data from the Egypt Labor Market Panel Survey 2012 (ELMPS). The ELMPS is a nationally representative panel survey carried out by the Economic Research Forum (ERF) in cooperation with Egypt’s Central Agency for Public Mobilization and Statistics (CAPMAS). The ELMPS is a nationally representative household survey with very rich information on labor market characteristics and dynamics.[[10]](#footnote-10) It was administered to nationally representative samples in 1998, 2006, and 2012.[[11]](#footnote-11) We focus particularly on the third round, the ELMPS 2012. The total sample size is 12,060 households and 49,186 individuals. We exploit rich information derived from a supplementary module on return migration, surveying individuals aged between 15 and 59 years old who have worked abroad for more than six months.[[12]](#footnote-12) This module features return migrants’ characteristics, incidence of migration, reasons for migration, year and country of first migration episode, year of final return, as well as other relevant information.

We focus mainly on the 1960s birth cohort, but also use different cohorts to check for the robustness of the results.[[13]](#footnote-13) We only focus on men, as we only have 2% of women returnees among those in the 1960s cohort. Throughout the analysis, we consider the year 2010 for the current occupation, before the 2011 Arab Spring protests, instead of 2012 (the time of the survey).[[14]](#footnote-14) Our 1960s cohort is comprised of 1,416 stayers and 328 returnees.[[15]](#footnote-15) A returnee is defined as an individual who worked abroad but returned to Egypt before 2010, whereas a stayer is defined as an individual who never had any overseas migration experience.

[Table 1 here]

Descriptive statistics on the sample of stayers and returnees in the 1960s cohort are reported in Table 1. In Panel A, we report descriptive statistics on the control variables that are included in our regressions, while in Panel B we report descriptive statistics on various occupational mobility indicators. Returnees are found to be two years younger compared to non-migrants at first job. In terms of educational attainment, we find that approximately 90% of return migrants had at least secondary education, compared to 76% of stayers. We also find a higher incidence of rural residency at birth among return migrants relative to non-migrants. Table 1 also sheds light on individuals’ first job characteristics. For their first occupation, we find that returnees are significantly more likely to be employed in economic activities such as agriculture and construction and less likely to be employed in wholesale and retail trade, relative to non-migrants. Return migrants are also found to be significantly more likely to work in the private sector, as opposed to non-migrants, who are significantly more likely to work in the public sector at first job. The incidence of work contract and social security at first job is also significantly lower among return migrants relative to stayers. Return migrants and stayers also exhibit different occupational distribution for their first job. Return migrants are more likely to be employed in agriculture and high-skilled blue-collar occupations, while non-migrants are more likely to be employed in low-skilled blue-collar occupations and white-collar occupations, both low-skilled and high-skilled.

* 1. **Occupational mobility**

In order to estimate occupational mobility, we compare each individual’s first occupation to his occupation in 2010.[[16]](#footnote-16) Occupational categories are split into five distinct categories, according to the ISCO-88 one digit classification. They are the following: agriculture, low-skilled blue-collar, high-skilled blue-collar, low-skilled white-collar, and high-skilled white-collar.[[17]](#footnote-17) These five occupational categories are ranked one to five, respectively. The occupational ranking reflects the earning progression by occupation, as shown in Table A1 in the Online Appendix, which reports the average hourly and monthly wages in Egyptian pounds by occupation.[[18]](#footnote-18)

While returnees on average seem to hold lower ranked occupations at first job, they are found to be significantly more likely to witness upward occupational mobility compared to stayers. In Table 1, Panel B, we show several occupational mobility indicators. Upward mobility is a dummy variable equal to one if the individual’s occupation in 2010 is ranked higher compared to his first job occupation, while the opposite is true for downward mobility. Immobility is a dummy variable equal to one if the individual stayed within the same occupational category in the two years considered. The degree of mobility ranges between -4 and 4 and is the difference between the 2010 occupational ranking and the first job occupational ranking. Indeed, we find that the incidence of occupational upgrading is 13 percentage points higher among return migrants relative to non-migrants. We also find that the likelihood of occupational immobility is significantly lower among return migrants while the degree of mobility is significantly larger.

[Table 2 here]

In order to examine the occupational mobility of the 1960s cohort, in Table 2, we construct employment transition matrices for stayers (Panel A) versus returnees (Panel B) between the first job and the 2010 job in Egypt. The diagonal cells represent the percentage of individuals who stayed within the same occupational category between the first job and the job in 2010. The cells above the diagonal represent the percentage of individuals who witnessed upward mobility, whereas the cells below the diagonal represent the percentage of individuals who witnessed downward mobility. Thus, the share of individuals witnessing upward mobility is equal to the sum of the cells above the diagonal. Among the sample of returnees in the 1960s cohort, we find that 42% of return migrants witnessed upward occupational mobility when we compare their first job and their job in 2010. This figure drops to 30% when we consider the sample of stayers.[[19]](#footnote-19) Interestingly, we also find that 40% of the returnees who witnessed upward mobility had either high-skilled blue-collar or low-skilled white-collar occupations at first job and they moved up the occupational ladder to hold either white-collar occupations in general for the former category or high-skilled white-collar occupations for the latter. Meanwhile, 64% of the stayers who witnessed upward occupational mobility had less qualified occupations to start, namely agricultural or low-skilled blue-collar occupations.

1. **Empirical strategy: An instrumental variable approach**

We estimate the effect of return migration on occupational mobility, focusing on the 1960s birth cohort. For each individual, we compare his first occupation to his occupation in 2010. Using a linear probability model, we estimate the following specification:

(1)

is a dummy variable for upward mobility that takes the value one if the individual’s occupation in 2010 is ranked higher compared to his first job occupation, and zero otherwise. Returnee is a dummy variable equal to 1 for men who had worked abroad for more than six months and returned to Egypt before 2010 and equal to zero for non-migrants. is a vector of pre-determined individual characteristics and it includes: age at birth, individual educational levels, a dummy variable for rural residence at birth, and a dummy variable for above intermediate parental education. is a vector of pre-determined first job characteristics and includes: sectors of employment, economic activities, the incidence of work contract, and social security. Importantly, we examine the impact of temporary migration experience on occupational upgrading given an individual’s first occupation, by controlling for first job occupation dummies. Moreover, we control for the initial GDP per capita in Egypt (at the time of the first job for stayers and at the time of migration for returnees) to account for the different business cycles hitting Egypt and return migrants’ destination countries.

An empirical challenge we face is that unobserved individual characteristics might simultaneously affect the probability of temporary migration on one hand, and occupational choices on the other. To address the endogeneity problem inherent in this analysis, we estimate equation (1), using an instrumental variable approach. To obtain an exogenous source of variation in the probability of temporary migration, we use historical inflation-adjusted oil prices as an instrument, following Wahba and Zenou (2012) and Bertoli and Marchetta (2015). Using a two-stage least squares procedure, oil prices are matched with the year when the individual was 26 years old, which is the mean age at migration for our sample of Egyptian men in the 1960s cohort.[[20]](#footnote-20)

[Figure 1 here]

The rationale behind using historical oil prices as a predictor of the migration probability, as argued by Wahba and Zenou (2012), is that other Arab countries constitute the most important destination for Egyptian migrants, and oil prices play a crucial role in driving the demand for foreign labor both directly in the oil producing countries or indirectly, as replacement workers, in non-oil Arab countries.[[21]](#footnote-21) In Figure 1, we present the evolution of inflation-adjusted oil prices and migration patterns from the 1960s to 2010. The share of migrants is derived from the ELMPS (2012), using information on both current and return migrants and the year of migration. This figure shows how the share of migrants varies in response to fluctuations in oil prices and that the two series are closely correlated and follow the same patterns.

[Figure 2 here]

The exclusion restriction is that oil prices affect occupational mobility only through temporary migration decision. The identifying assumption is that controlling for individuals’ first occupations, and for the different business cycles of Egypt and the oil producing countries, oil prices when individuals are aged 26 years old are not correlated with occupations in Egypt, a non-oil dependent economy. We show evidence in Figure 2, which presents the relationship between oil prices and occupations in Egypt, to support our exclusion restriction. To this end, we rely on all the available ELMPS survey rounds and examine the correlation between oil prices, over the course of 30 years between 1988 and 2018, and the occupational distribution of Egyptian men aged between 15 and 59 years old. Indeed, this figure shows no association between oil prices and the occupational distribution in Egypt, in both stocks and flows. This figure displays no discernible changes in men’s occupational distribution in relation to oil price fluctuations. Finally, it is important to note that we consider individuals born in the 1960s and that oil prices at the age 26 are unlikely to be correlated with occupations in Egypt in 2010, when individuals are aged between 40 and 50 years old.[[22]](#footnote-22)

In Figure A1 in the Online Appendix, we also present oil prices against key aggregate economic indicators in Egypt, including GDP annual growth rate, male labor force participation rate, male employment in agriculture (% of total male employment), male employment in industry (% of total male employment) and male employment in services (% of total male employment).[[23]](#footnote-23) This figure shows that key economic labor market indicators in Egypt are irresponsive to oil prices and do not seem to be affected by oil price fluctuations, providing additional support for our exclusion restriction.

[Table 3 here]

In Table 3, we report first stage regressions for the 1960s cohort. We match the inflation-adjusted oil prices with the mean age at migration for our sample (26 years of age), but also use one year below and one year above the mean age for robustness. Our first stage results show that our instrument is well correlated with the endogenous variable. On average, we find that one dollar rise in the price of oil increases the probability of being a returnee by 3 percentage points. We also check the robustness of our IV (real oil prices) when we account for within community correlation, by clustering our regressions at the community (*shyakha*) level, which corresponds to the smallest administrative unit in Egypt.[[24]](#footnote-24) Additionally, we account for common shocks across individuals with the same year of birth, and hence similar values of oil prices, by clustering our regressions by year of birth. Table A2 in the Online Appendix shows the first stage regressions using these different clustering techniques. These results are robust and consistent with the first stage regressions in Table 3.

1. **Empirical Findings**
   1. **Does return migration lead to occupational upgrading?**

[Table 4 here]

We estimate the effect of return migration on upward occupational mobility relying on the 1960s birth cohort. In Table 4, we estimate Equation 1 using linear probability and IV-regression models. In columns (1) and (2), we condition on the individual and first job characteristics presented in Section 3, while in columns (3) and (4) we also control for the first occupation. We find a positive and statistically significant effect of return migration on upward occupational mobility for men who belong to the same birth cohort. The finding is robust across all specifications. More specifically, controlling for the first occupation and correcting for the endogeneity of the migration decision, we find that being a return migrant increases the probability of upward occupational mobility by 16 percentage points. Not controlling for the first occupation would lead us to overestimate the effect of return migration on occupational upgrading. This is likely due to the fact that stayers seem to have on average higher ranked occupations at first job, while returnees have on average lower ranked first occupations. Therefore, not accounting for the first occupations would lead to an upward bias in our estimates of returnees’ occupational upgrading vis-à-vis non-migrants.

* 1. **Heterogeneous effects: Who climbs the occupational ladder?**

[Table 5 here]

We explore the heterogeneity of the effect of return migration on occupational upgrading with respect to individual’s education and migration duration. We split our 1960s cohort into two groups: the less educated (those with less than secondary education) and the more educated (those with secondary education and above). We report results for these two groups using IV regressions along with linear probability model estimates in Table 5 and controlling for the same set of covariates presented earlier. Our results show that return migration is associated with occupational upgrading among both groups, given an individual’s first occupation. However, we estimate a greater likelihood of occupational upgrading among the most educated individuals. Relying on our IV regressions, we find that return migration leads to an increase in the probability of upward occupational mobility by 16 percentage points among the most educated, while it leads to an increase in the probability of occupational upgrading by 13 percentage points among the least educated. Our results therefore showcase that men who belong to the upper end of the educational distribution are more likely to witness upward occupational mobility.

[Table 6 here]

Furthermore, we investigate the heterogeneity of the effect of return migration on occupational upgrading by migration duration. On average returnees in our sample spent 4.5 years overseas, and the median migration duration is equal to 2.5 years. In Table 6, we provide predicted probabilities of upward mobility and the standard errors relying on our benchmark model, for the full sample of stayers in the 1960s cohort, for the full sample of returnees, and for returnees by migration duration. In line with previous results, we find that returnees have a higher predicted probability of witnessing upward mobility compared to non-migrants. Moreover, we find that the positive effect of return migration on occupational upgrading is larger the longer the duration of the migration experience. Indeed, individuals with 7 years of migration experience or more witness a higher probability of occupational upgrading relative to individuals with one year of migration experience or less but also relative to individuals who belong to the middle of the migration duration distribution. These findings suggest that our results seem to be driven by human capital enhancement of returnees, in particular for the highly educated, resulting in upward occupational mobility upon return to their home country.

1. **Robustness checks**
   1. **Robustness checks using alternative estimation techniques**

Our benchmark model relies on an instrumental variable approach to estimate the effect of return migration on occupational upgrading, while accounting for the endogeneity of temporary migration decision. In this section, we also show that our results are robust to using alternative estimation techniques, such as an IV ordered probit model or a Difference-in-Differences matching technique.

[Table 7 here]

**An IV ordered probit model:** In our benchmark model, our independent variable is a dummy variable indicator for upward occupational upgrading. In this section, we estimate an ordered probit model. Our independent variable is a categorical variable equal to 0 if the individual stayed within the same occupational category or downgraded between the first job and the 2010 occupation; equal to 1 if the individual moved up the occupational ladder one step; equal to 2 if the individual moved up the occupational ladder two steps; and equal to 3 if the individual climbed up the occupational ladder three or four steps. We control for the same set of covariates presented in Section 3 and report the results in Table 7. In Panel A, we rely on an ordered probit model. In Panel B, we show results using an IV ordered probit model, while in Panel C, we additionally bootstrap the standard errors.

Relying on the IV-ordered probit model in Panel B, we find that return migration decreases the probability of occupational downgrading or immobility by 13 percentage points. We also find that return migrants have a consistently higher probability of leaping across occupational categories, by moving up the occupational ladder either one step, two steps, or even three or four steps. Interestingly, returnees also have a higher probability of making bigger leaps across the occupational ladder compared to stayers: 7 percentage points for moving up the occupational ladder 3 or 4 steps, compared to 4 percentage points for moving up two steps, and 3 percentage points for moving up 1 step. These results are consistent with those reported in Panel C, when using an IV-ordered probit model with bootstrapped standard errors.

**A Difference-in-Differences matching technique:** We also estimate a Difference-in-Differences matching technique that allows for a within comparison between stayers and returnees, while controlling for unobserved time-invariant heterogeneity between the two groups. First, we estimate the propensity score or the individual’s probability of receiving the treatment based on the same set of covariates presented in Section 3, as illustrated in equation (2). The treatment corresponds to return migration. Therefore, the treatment group refers to return migrants in the 1960s cohort, while the control group corresponds to stayers of the same cohort. We estimate the propensity score with and without controlling for the first job occupations and report both sets of results. The propensity score matching enables us to pair return migrants with stayers who have similar values of the propensity score. Therefore, aside from the treatment, the two groups after the matching are similar in terms of observable characteristics. To estimate the propensity score, we rely on a standard nearest neighbor matching technique, following Abadie and Imbens (2006). Our matching technique is without replacement, which means that an untreated unit can only be used once as a match. This is a well-adapted technique since we have a large number of untreated units relative to treated units (Caliendo and Kopeinig, 2008). The key assumption for propensity score matching, illustrated in Equations (2a) and (2b), is that the outcome is orthogonal to treatment assignment (denoted by ) conditional on .

(2)

(2a)

(2b)

Second, we combine the propensity score matching with a standard Difference-in-Differences specification, based on the matched sample of returnees and stayers relying on equation (3). is the individual’s occupation at time *t,* split into five distinct occupational categories, according to the one digit ISCO-88 classification: agriculture, low-skilled blue-collar, high-skilled blue-collar, low-skilled white-collar, and high-skilled white-collar. is a dummy variable equal to one for the sample of returnees and to zero for the sample of stayers in the 1960s cohort. is a dummy variable equal to one in 2010 and equal to zero for the first job. The time dummy captures aggregate factors that could cause changes in the individual occupations even in the absence of the treatment. Equation (3) also includes a dummy variable for each pair of matched stayer and returnee, , to allow for a within comparison between stayers and returnees with similar propensity score values. The coefficient of interest is : it multiplies the interaction term between the treatment variable and the time period dummy. The Difference-in-Differences estimator in Equation (3a) is the difference in the average occupational ranking among the returnees between the follow-up and the baseline periods, minus the difference in the average occupational ranking among the stayers for the same periods. It differences out all unobserved time-invariant differences between the treatment and control groups.

(3)

(3a)

In Figure A2 in the Online Appendix, we produce a kernel density plot of the propensity score to check the balancing property of the matching. Whereas the density plots in the raw data show significant differences between treated and untreated units, the matching led to significant reduction in the gap between the two groups. Indeed, for the most part of the distribution, the density plots for the matched sample are nearly indistinguishable, implying that matching on the estimated propensity score balanced the covariates. In Table A3 in the Online Appendix, we also check the covariate balance for treated and untreated units, before and after the matching. The raw data shows significant differences between the two groups in terms of individual but also in terms of first job characteristics. After the matching, the two groups, stayers and returnees, are very comparable across all characteristics. This suggests that the matching technique successfully achieved covariate balance between the two groups.

[Table 8 here]

The results from the Difference-in-Differences matching technique are reported in Table 8. In Panel A, we compute the propensity score based on the full set of controls presented in Section 3, without controlling for first job occupations dummies, while in Panel B we additionally control for the first occupations when computing the propensity score. Using a matching Difference-in-Differences specification, we find that return migration leads to a significant increase in occupational upgrading. Both specifications with and without controlling for first occupations lead to consistent estimates in line with our benchmark model results presented in Section 4.1.[[25]](#footnote-25)

* 1. **Robustness checks related to the benchmark IV-regression model**

[Table 9 here]

In this section, we perform various robustness checks related to our benchmark model. First, we check the robustness of our results with respect to the IV regression model’s specification. In our benchmark model, we control for pre-determined individual and first job characteristics including the first occupations. In Table 9, in column (1), we also report results excluding the vector of first job characteristics, while also controlling for pre-determined individual characteristics. In Table 9, in column (2), we control for years of entry in the labor market fixed effects for the 1960s cohort, in addition to controlling for individual and first job characteristics, as well as first occupations. The latter robustness check allows us to control for the initial labor market conditions. Our results are robust to these two checks.

Second, we provide robustness checks related to the exclusion of oil prices in Table 9, in columns (3) and (4). We use two different clustering techniques: community level clustering (the smallest administrative unit in Egypt) or year of birth clustering (since individuals with the same year of birth are matched with the same value of oil prices). Clustering our regressions at the year of birth allows us to account for common shocks across individuals with the same year of birth. Our results are consistently robust to using both clustering techniques and are very stable in terms of magnitude.

Third, we check the robustness of our results with respect to aggregating and disaggregating the occupational categories. In Table 9 in column (5), we use a more aggregated definition, where occupations are split into 3 occupational categories: agriculture, blue-collar occupations, and white-collar occupations (ranked 1 to 3, respectively). In column (6), we instead use a more disaggregated definition, where occupations are split into 6 occupational categories: agriculture, blue-collar, low-skilled white-collar, technicians and associate professionals, legislators and managers, and professionals (ranked 1 to 6 respectively).[[26]](#footnote-26) Our results are robust to using the two levels of aggregation. Related to the occupation definition, in Table 9 in column (7), we exclude all individuals who had high-skilled white-collar occupations at first job, since by definition they cannot move up the occupational ladder between the first occupation and the 2010 occupation. Our results are also robust to eliminating men who started their career with high-skilled white-collar occupations and actually become even larger in magnitude.

* 1. **Robustness checks related to the underlying mechanism**

Our results provide empirical evidence suggesting that returnees accumulate human capital during their migration experience abroad. In this section, we discuss other potential channels through which return migration could lead to upward occupational mobility.

First, we investigate whether physical capital accumulation could be driving the occupational upgrading. Since returnees accumulate savings while overseas, we restrict our sample to wage workers only to check that occupational mobility is indeed driven by human capital accumulation rather than by setting-up business or entrepreneurial activities in Egypt. In Table 9 in column (8), we restrict our analysis to wage workers in 2010, while in column (9) we focus on wage workers during both the first and the 2010 occupation. Our results are robust to restricting our analysis to wage workers. These results rule out the possibility that our results might be driven by physical capital accumulation, since we are only focusing on wage workers and thus eliminating entrepreneurs, whether they are employers or self-employed.[[27]](#footnote-27)

Second, we explore whether internal migration in Egypt and returnees’ locational choices upon return could explain our results. In Table A5 in the Online Appendix, we present internal mobility matrices. We look at the geographical mobility of stayers and returnees, born in the 1960s, between their geographical region of birth and their current geographical region. We do so to ensure that the positive occupational mobility witnessed by the returnees is not driven by their locational choices in Egypt, upon return. First, we find that both stayers and returnees were equally mobile, with only around 7% of the stayers and 6% of the returnees relocating in a different geographical region compared to their geographical region of birth.[[28]](#footnote-28) We also find that in their current geographical region, stayers are more likely to be located in bigger cities like Cairo, Alexandria, and Canal Cities, with greater work opportunities compared to returnees (22% of stayers compared to 11% of returnees). We also find the same patterns at birth, with 20% of stayers and 10% of returnees located in Cairo, Alexandria, and Canal cities. This confirms that the returnees’ higher incidence of occupational upgrading relative to stayers is not driven by their locational choices upon return for two reasons: first, both stayers and returnees were found to be equally mobile within Egypt; second, stayers were found to relocate to the capital and bigger cities compared to returnees, who were found to be more likely to relocate to rural regions in Lower and Upper Egypt.

Finally, we investigate the issue of repeated migration, as individuals might be taking, on a repeated basis, the decision to migrate or not. This decision might be motivated by their occupational draw after they return to Egypt. From a conceptual point of view, repeated migration could be an issue if those with a single migration episode are also those who had better occupational draw upon return to Egypt, while those who embarked on repeated migration experiences are those who had poorer occupations upon return. To investigate whether repeated migration could be driving our results, we use a recent ELMPS survey round conducted in Egypt in 2018. This allows us to observe attrition between 2012 and 2018 and particularly to examine whether return migrants in the 1960s cohort decided to migrate again. We report in Table A6 the attrition rates (Panel A) and individual attrition results (Panel B) for the entire 2012 sample and for returnees in the 1960s cohort. For the full 2012 sample, we find an attrition rate of 20% between 2012 and 2018, while the attrition rate among returnees in the 1960s cohort is only 13%. The individual attrition results are reported in Panel B. This panel provides information on whether the individual was retrieved in the original household or in split households. It also provides information on whether: the individual split to form a new household that was not found, died, emigrated, moved to group housing, belongs to a household that either refused to answer the questionnaire, did not complete the questionnaire or was not located. Indeed, we find that the incidence of emigration between 2012 and 2018 is too low (2% for the full sample and 1% for returnees in the 1960s cohort). Moreover, we find that the incidence of a household not being located among the 1960s cohort, which might be due to many reasons but does not rule out the possibility of emigration, is equal to 5% for returnees in the 1960s cohort (less than the corresponding rate for the full 2012 survey sample, which is equal to 9%). These results therefore suggest that repeated migration episodes are actually quite limited.[[29]](#footnote-29) Furthermore, in Table A7 in the Online Appendix, we examine the 2010 occupational distribution of returnees in the 1960s cohort depending on whether they were successfully interviewed or not in 2018. We also report in column (5) the difference in means between the two groups, as well as a t-test for whether the difference in means between columns (1) and (3) is statistically significant. Indeed, we find that returnees who were not successfully interviewed in 2018 hold on average better ranked occupations in 2010 compared to returnees who were successfully interviewed in 2018. For instance, the incidence of agricultural occupations is lower among returnees who were not successfully tracked in 2018, while the incidence of high-skilled white collar occupations is higher. However, the difference between the two groups is not statistically significant. Overall, these findings suggest that returnees who were not successfully interviewed in 2018 have comparable occupations relative to those who were interviewed in 2018. These findings therefore confirm that our results are not driven by repeated migration episodes whereby returnees with poorer occupational draws upon return decide to migrate again, driving up the occupational upgrading. If anything, the results suggest that returnees who were not successfully interviewed in 2018 have on average better ranked occupations upon return.

* 1. **Robustness checks using a different cohort**

In this section, we also rely on the 1950s birth cohort to provide some robustness checks with respect to the choice of the birth cohort under study.[[30]](#footnote-30) We focus on men who were born in the 1950s and were working in Egypt in 2010.[[31]](#footnote-31) In the Online Appendix Table A8, we estimate the effect of return migration on occupational mobility for the 1950s cohort. We rely on linear probability and IV-regressions using historical inflation-adjusted oil prices. Controlling for the first occupations and using an IV-regression model, we find that return migration leads to an increase in the probability of upward occupational mobility by 11 percentage points. In the Online Appendix Table A9, we also report results using a Difference-in-Differences matching technique using the same set of covariates presented in Section 3 to predict the propensity score. Controlling for matched pairs’ fixed effects that allow for a within comparison between each pair of matched stayer and returnee, we consistently find that return migration experience leads to upward occupational upgrading for the 1950s birth cohort. Our findings can therefore be viewed as robust to using alternative birth cohorts.[[32]](#footnote-32)

1. **Conclusion**

We study the human capital accumulation of return migrants in Egypt and the extent to which their overseas migration experience enables them to climb up the occupational ladder upon return. Relying on birth cohort analysis, we compare an individual’s first occupation with his occupation in 2010, and study the effect of overseas work experience on the occupational trajectories of return migrants relative to stayers. We use an instrumental variable approach to deal with the endogeneity of the temporary migration decision, and find that return migration increases the probability of upward occupational mobility. Our results also indicate greater occupational upgrading among highly educated return migrants.

Egypt is an especially interesting case, due to the high incidence of return migration. We show that return migration in Egypt can be beneficial since it can allow the return migrants’ population to upskill and hold better occupations upon return. Our findings also support the qualitative evidence from the European Training Foundation (ETF) survey, which suggests that overseas experiences helped migrants acquire skills and find better work since returning.

Our analysis further allows us to draw some nuanced conclusions as to when and how our results might be generalized to other developing countries. Indeed, returnees can constitute a highly diverse group, as they can display different characteristics and motives. Migrants can be skilled or unskilled, highly educated or less educated, and they may choose to migrate for economic, cultural or political reasons. Our paper provides evidence on economic migrants who eventually returned to their origin country. As migrants acquire human capital and skills during their migration experiences abroad, our findings could help inform research on similar settings of economic migration in other developing and transition economies, particularly those with high return migration rates. Refugee return migrants, on the other hand, may not experience equally beneficial outcomes. As Fransen, Ruiz and Vargas-Silva (2017) point out, in the case of Burundi, refugee return migration is associated with a deterioration in returnees’ economic outcomes, due to the legal restrictions on economic activities they experienced while in displacement, which may lead to the loss or deterioration of their skills. Whether all types of returnees witness occupational upgrading upon return also hinges upon the labor market conditions of the origin developing countries. In our study, we find evidence that returnees climb up the occupational ladder upon return since they acquired skills abroad that were highly rewarded in the Egyptian labor market. However, if origin labor markets or certain sectors of employment are underdeveloped or not equipped to make use of return migrants’ skills, or if the human capital accumulated abroad is not transferable, we might expect different results. This was indeed highlighted in Black and King (2004) and Coniglio and Brzozowski (2018).

Focusing on an understudied mechanism through which return migration can lead to a brain gain, this paper shows evidence that return migration allows home countries to upskill, and can drive economic development. An important implication of our findings is that concerns about brain drain might be exaggerated, as the evidence clearly shows the significance of return migration, as well as the potential of overseas human capital accumulation. This suggests that temporary migration could indeed enhance human capital and economic development in origin developing countries.

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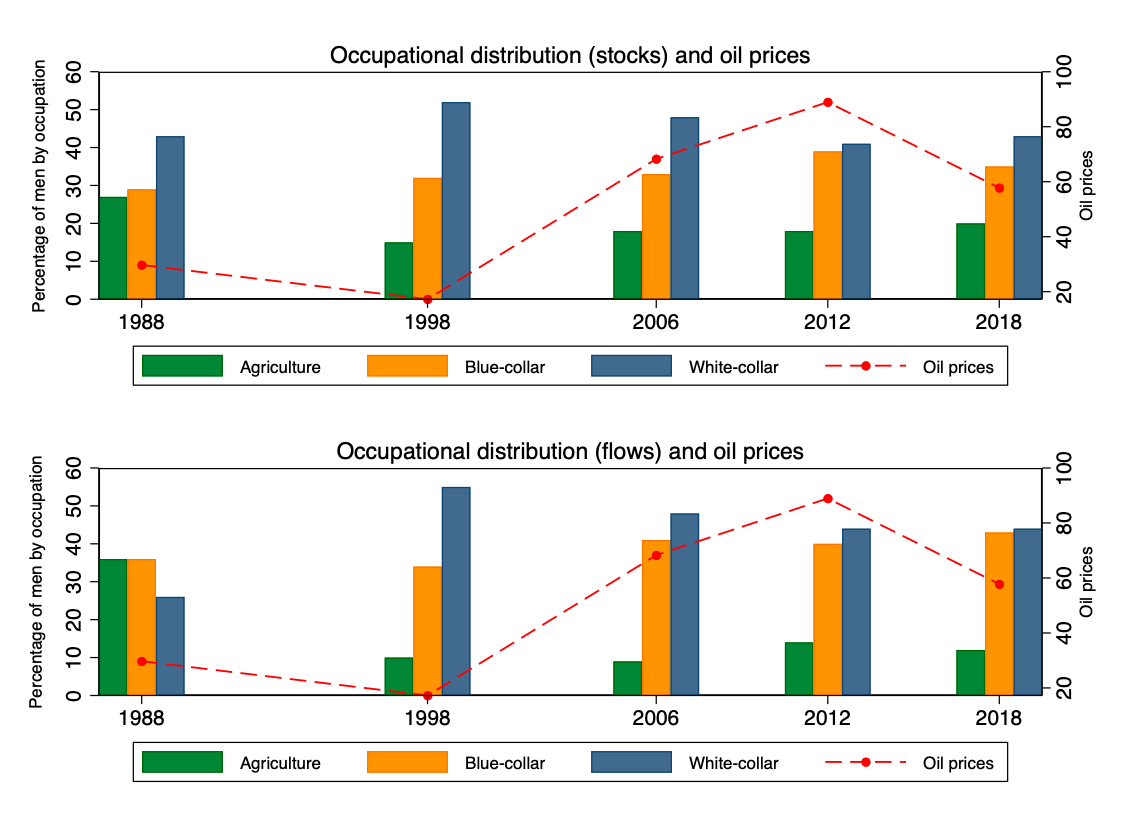
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**Figure 1*.* Oil prices and migration patterns from the 1960s to 2010.**

*Notes.* Oil prices are inflation adjusted and expressed in $ per Barrel (primary Y-axis). Migration patterns are derived from the ELMPS 2012, using information on current, return migration, and the year of migration. They are expressed as the share of migrants in a specific year to the total migrants (secondary Y-axis).



**Figure 2*.* Oil prices and occupational distribution from the 1988 to 2018.**

*Notes.* This figure plots men’s occupational distribution relying on data from the Egypt Labor Market Panel Surveys in the years 1988, 1998, 2006, 2012, and 2018 (primary Y-axis). On the primary Y-axis, we plot the share of men employed in each of the occupational categories (agriculture, blue-collar, and white collar occupations). In the top panel, we report stocks, while in the lower panel, we report flows in the corresponding survey year. Oil prices are inflation adjusted and expressed in $ per Barrel (secondary Y-axis).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 1: Descriptive statistics on the control variables** | | | | | | |
|  |  | **Stayers** | | **Returnees** | |  |
|  |  | (1) | (2) | (3) | (4) | (5) |
| VARIABLES | | Mean | St. Dev. | Mean | St. Dev. | Difference |
| **Panel A: Control variables** | |  |  |  |  |  |
| ***Individual characteristics*** | |  |  |  |  |  |
| Age at first job | | 17.744 | 5.969 | 15.375 | 4.599 | 2.369\*\*\* |
| Secondary or less education | | 0.763 | 0.426 | 0.896 | 0.305 | -0.134\*\*\* |
| Above secondary education | | 0.237 | 0.426 | 0.104 | 0.305 | 0.134\*\*\* |
| Rural at birth | | 0.520 | 0.500 | 0.665 | 0.473 | -0.145\*\*\* |
| Above intermediate parental education | | 0.024 | 0.153 | 0.006 | 0.078 | 0.018\*\* |
|  |  |  |  |  |  |  |
| ***First job characteristics*** | |  |  |  |  |  |
| *Economic activity* | |  |  |  |  |  |
| Agriculture, Forestry, Fishing | | 0.309 | 0.462 | 0.433 | 0.496 | -0.124\*\*\* |
| Manufacturing, Mining, Quarrying | | 0.148 | 0.355 | 0.116 | 0.321 | 0.032 |
| Construction | | 0.119 | 0.323 | 0.22 | 0.415 | -0.101\*\*\* |
| Wholesale, retail trade, transportation and other activities | | 0.219 | 0.414 | 0.128 | 0.335 | 0.091\*\*\* |
| Professional, scientific and administrative activities | | 0.018 | 0.132 | 0.027 | 0.164 | -0.010 |
| Other activities | | 0.189 | 0.391 | 0.076 | 0.266 | 0.112\*\*\* |
|  |  |  |  |  |  |  |
| *Sector of employment* | |  |  |  |  |  |
| Public | | 0.220 | 0.414 | 0.098 | 0.297 | 0.122\*\*\* |
| Private | | 0.780 | 0.414 | 0.902 | 0.297 | -0.122\*\*\* |
|  |  |  |  |  |  |  |
| *Incidence of work contract and social security* | |  |  |  |  |  |
| Work contract | | 0.256 | 0.437 | 0.098 | 0.297 | 0.159\*\*\* |
| Social security | | 0.265 | 0.441 | 0.079 | 0.271 | 0.186\*\*\* |
|  |  |  |  |  |  |  |
| *First job occupation* | |  |  |  |  |  |
| Agriculture | | 0.306 | 0.461 | 0.43 | 0.496 | -0.124\*\*\* |
| Low-skilled blue-collar | | 0.122 | 0.328 | 0.067 | 0.251 | 0.055\*\*\* |
| High-skilled blue-collar | | 0.209 | 0.407 | 0.326 | 0.470 | -0.117\*\*\* |
| Low-skilled white-collar | | 0.116 | 0.32 | 0.079 | 0.271 | 0.037\* |
| High-skilled white-collar | | 0.247 | 0.432 | 0.098 | 0.297 | 0.150\*\*\* |
|  |  |  |  |  |  |  |
| **Panel B: Mobility indicators** | |  |  |  |  |  |
| Upward mobility | | 0.298 | 0.458 | 0.424 | 0.495 | -0.126\*\*\* |
| Downward mobility | | 0.083 | 0.275 | 0.091 | 0.289 | -0.009 |
| Immobility | | 0.619 | 0.486 | 0.485 | 0.501 | 0.135\*\*\* |
| Degree of mobility | | 0.483 | 1.247 | 0.729 | 1.415 | -0.246\*\*\* |
|  |  |  |  |  |  |  |
| Number of observations | | 1,416 | | 328 | |  |

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Column 5: is t-test for whether the difference in means between the two groups is statistically significant.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Employment transition Matrices for Stayers versus Returnees in the 1960s cohort** | | | | | | |
|  | Current occupation | | | | |  |
| First occupation | Agriculture | Low-skilled blue-collar | High-skilled blue-collar | Low-skilled white-collar | High-skilled white-collar | Total |
| **Panel A: Stayers (N=1,416)** | | | | | | |
| Agriculture | 16.031 | 5.932 | 1.836 | 2.613 | 4.167 | 30.579 |
| Low-skilled blue-collar | 0.353 | 7.486 | 0.777 | 0.989 | 2.613 | 12.218 |
| High-skilled blue-collar | 0.565 | 3.814 | 9.816 | 1.836 | 4.873 | 20.904 |
| Low-skilled white-collar | 0.071 | 1.130 | 0.494 | 5.720 | 4.167 | 11.582 |
| High-skilled white-collar | 0.071 | 0.494 | 0.847 | 0.424 | 22.881 | 24.718 |
| Total | 17.090 | 18.856 | 13.771 | 11.582 | 38.701 | 100.000 |
| **Panel B: Returnees (N=328)** | | | | | | |
| Agriculture | 21.646 | 8.537 | 3.049 | 2.744 | 7.012 | 42.988 |
| Low-skilled blue-collar | 0.305 | 2.439 | 0.610 | 0.915 | 2.439 | 6.707 |
| High-skilled blue-collar | 1.524 | 4.573 | 13.720 | 3.963 | 8.841 | 32.622 |
| Low-skilled white-collar | 0.305 | 0.610 | 0.915 | 1.829 | 4.268 | 7.927 |
| High-skilled white-collar | 0.000 | 0.915 | 0.000 | 0.000 | 8.841 | 9.756 |
| Total | 23.780 | 17.073 | 18.293 | 9.451 | 31.402 | 100.000 |

*Notes.* The diagonal cells represent the percentage of individuals who stayed in the same occupational category between the first job and the job in 2010. The cells above the diagonal represent the percentage of individuals who witnessed upward mobility, whereas the cells below the diagonal represent the percentage of individuals who witnessed downward mobility.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 3: First stage regressions** | | | |
|  | (1) | (2) | (3) |
| VARIABLES | Return migrant | Return migrant | Return migrant |
|  |  |  |  |
| Oil price at age 25 | 0.024\*\*\* |  |  |
|  | [0.001] |  |  |
| Oil price at age 26 |  | 0.029\*\*\* |  |
|  |  | [0.000] |  |
| Oil price at age 27 |  |  | 0.029\*\*\* |
|  |  |  | [0.000] |
|  |  |  |  |
| Observations | 1,744 | 1,744 | 1,744 |
| Individual controls | YES | YES | YES |
| First job characteristics | YES | YES | YES |
| First occupation | YES | YES | YES |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Coefficient estimates for first stage IV-regressions are reported. We use the inflation-adjusted oil prices when the individual was 26 years old (the mean age at migration in our estimation sample). For robustness, we also tried to match the oil prices at age 25 and age 27.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 4: Estimating the effect of return migration on occupational mobility** | | | | |
|  | (1) | (2) | (3) | (4) |
|  | Linear probability model | IV-Regression | Linear Probability Model | IV-Regression |
| VARIABLES | Upward mobility | Upward mobility | Upward mobility | Upward mobility |
|  |  |  |  |  |
| Return migrant | 0.152\*\*\* | 0.165\*\*\* | 0.144\*\*\* | 0.158\*\*\* |
|  | (0.036) | (0.037) | (0.034) | (0.035) |
|  |  |  |  |  |
| Observations | 1,744 | 1,744 | 1,744 | 1,744 |
| R-squared | 0.131 | 0.130 | 0.183 | 0.183 |
| Individual controls | YES | YES | YES | YES |
| First job characteristics | YES | YES | YES | YES |
| First occupation | NO | NO | YES | YES |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Coefficient estimates are reported using linear probability and IV regression models.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 5: Investigating the heterogeneity of the effect of return migration on upward occupational mobility**  **by educational attainment** | | | | |
|  | **Less educated** | | **More educated** | |
|  | (1) | (2) | (3) | (4) |
|  | Linear probability model | IV-Regression | Linear Probability Model | IV-Regression |
| VARIABLES | Upward mobility | Upward mobility | Upward mobility | Upward mobility |
|  |  |  |  |  |
| Return migrant | 0.107\*\* | 0.125\*\* | 0.149\*\*\* | 0.162\*\*\* |
|  | (0.051) | (0.053) | (0.042) | (0.042) |
|  |  |  |  |  |
| Observations | 877 | 877 | 867 | 867 |
| R-squared | 0.064 | 0.064 | 0.436 | 0.435 |
| Individual controls | YES | YES | YES | YES |
| First job characteristics | YES | YES | YES | YES |
| First occupation | YES | YES | YES | YES |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Coefficient estimates are reported using a linear probability and IV-regression models. The less educated individuals are those who have less than secondary education and the more educated individuals are those who have secondary education and above.

|  |  |
| --- | --- |
| **Table 6: Predicted probabilities and standard errors for stayers and returnees, by migration duration** | |
|  | Average predicted probabilities |
| Stayers | 0.296 |
|  | (0.037) |
| Returnees | 0.431 |
|  | (0.044) |
| Returnees (1 year or less) | 0.410 |
|  | (0.047) |
| Returnees (2 to 6 years) | 0.428 |
|  | (0.043) |
| Returnees (7 years or more) | 0.463 |
|  | (0.042) |

*Notes.* Average predicted probabilities and their standard errors are reported for stayers and returnees. We also report average predicted probabilities for returnees by migration duration. Predicted probabilities are derived from IV regressions, where oil prices are used to instrument for temporary migration decision.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 7: Robustness checks using ordered Probit and IV-ordered Probit Model** | | | | |
|  | (1) | (2) | (3) | (4) |
| **Panel A: Ordered Probit Model** | | | | |
| VARIABLES | Downward mobility (0) | Upward mobility (1) | Upward mobility (2) | Upward mobility (3) |
|  |  |  |  |  |
| Return migrant | -0.155\*\*\* | 0.043\*\*\* | 0.044\*\*\* | 0.069\*\*\* |
|  | (0.036) | (0.009) | (0.010) | (0.018) |
|  |  |  |  |  |
| **Panel B: IV Ordered Probit Model** | | | | |
|  |  |  |  |  |
| Return migrant | -0.134\*\*\* | 0.031\*\*\* | 0.035\*\*\* | 0.069\*\*\* |
|  | (0.030) | (0.007) | (0.008) | (0.016) |
|  |  |  |  |  |
| **Panel C: IV Ordered Probit Model with bootstrapped standard errors Controlling for the first occupation** | | | | |
|  |  |  |  |  |
| Return migrant | -0.151\*\*\* | 0.025\*\*\* | 0.042\*\*\* | 0.072\*\*\* |
|  | (0.041) | (0.008) | (0.013) | (0.022) |
|  |  |  |  |  |
| Observations | 1,744 | 1,744 | 1,744 | 1,744 |
| Individual controls | YES | YES | YES | YES |
| First job characteristics | YES | YES | YES | YES |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Marginal effects are reported for ordered probit and IV-ordered probit models. The (0) category refers to staying in the same occupation between the first job and the 2010 job, or downgrading. The (1) category refers to moving up the occupational ladder one step. The (2) category refers to moving up the occupational ladder two steps. The (3) category refers to moving up the occupational ladder 3 or 4 steps.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table 8: Robustness checks using Propensity Score Matching combined with Difference-in-Differences** | | | |
| **Panel A: Propensity score matching combined with Difference-in-Differences** | | | |
| **Sample of Returnees=324, Sample of Stayers=324** | | | |
|  | *Before the treatment* | *After the treatment* | *Difference* |
|  | *(t=0)* | *(t=1)* |
| *Returnees* | 2.346 | 3.080 | 0.735\*\*\* |
| *(Treatment group)* | (0.076) | (0.088) | (0.079) |
|  |  |  |  |
| *Stayers* | 2.528 | 3.015 | 0.488\*\*\* |
| *(Control group)* | (0.078) | (0.083) | (0.072) |
|  |  |  |  |
| *Difference* | -0.182\* | 0.065 | 0.247\* |
| (0.105) | (0.115) | (0.144) |
| **Panel B: Propensity score matching combined with Difference-in-Differences, Matching on the first occupation** | | | |
| **Sample of Returnees=325, Sample of Stayers=325** | | | |
|  | *Before the treatment* | *After the treatment* | *Difference* |
|  | *(t=0)* | *(t=1)* |
| *Returnees* | 2.348 | 3.083 | 0.735\*\*\* |
| *(Treatment group)* | (0.075) | (0.087) | (0.079) |
|  |  |  |  |
| *Stayers* | 2.511 | 2.969 | 0.458\*\*\* |
| *(Control group)* | (0.077) | (0.082) | (0.072) |
|  |  |  |  |
| *Difference* | -0.163 | 0.114 | 0.277\* |
| (0.100) | (0.119) | (0.142) |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Panel A provides estimates from Propensity Score Matching, using the nearest neighbor estimator combined with Difference-in-Differences. Individuals are matched based on their age at first job, educational attainment, rural at birth, and first job characteristics, including economic activities, sector of employment, incidence of work contract, and social security. In Panel B, we additionally match individuals based on their first job occupation. In both Panel A and Panel B, the regressions include a dummy variable for each pair of matched stayer and returnee. Before the treatment refers to the first occupation and after the treatment refers to the occupation in 2010. The dependent variable is the individual’s occupation ranking. It takes values from 1 to 5 for the following categories, respectively: agriculture, low-skilled blue-collar, high-skilled blue-collar, low-skilled white-collar, and high-skilled white-collar.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 9: Robustness checks, estimating the effects of return migration on upward occupational mobility** | | | | | | | | | |
|  | *Eliminating the vector of first job controls* | *Controlling for years of entry fixed effects* | *Clustering*  *at community level* | *Clustering*  *at year of birth level* | *Aggregating occupational categories* | *Disaggregating occupational categories* | *Eliminating high-skilled white collar at first job* | *Focusing on wage workers in the 2010 occupation* | *Focusing on wage workers in first job*  *& in 2010 occupation* |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|  | IV-Regression | IV-Regression | IV-Regression | IV-Regression | IV-Regression | IV-Regression | IV-Regression | IV-Regression | IV-Regression |
| VARIABLES | Upward mobility | Upward mobility | Upward mobility | Upward mobility | Upward mobility | Upward mobility | Upward mobility | Upward mobility | Upward mobility |
|  |  |  |  |  |  |  |  |  |  |
| Return migrant | 0.107\*\*\* | 0.156\*\*\* | 0.158\*\*\* | 0.158\*\*\* | 0.123\*\*\* | 0.052\*\* | 0.187\*\*\* | 0.152\*\*\* | 0.150\*\*\* |
|  | (0.031) | (0.041) | (0.034) | (0.031) | (0.032) | (0.023) | (0.040) | (0.039) | (0.045) |
|  |  |  |  |  |  |  |  |  |  |
| Observations | 1,744 | 1,744 | 1,744 | 1,744 | 1,744 | 1,744 | 1,362 | 1,223 | 1,041 |
| R-squared | 0.030 | 0.197 | 0.183 | 0.183 | 0.229 | 0.636 | 0.080 | 0.341 | 0.265 |
| Individual controls | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| First job characteristics | NO | YES | YES | YES | YES | YES | YES | YES | YES |
| First occupation | NO | YES | YES | YES | YES | YES | YES | YES | YES |

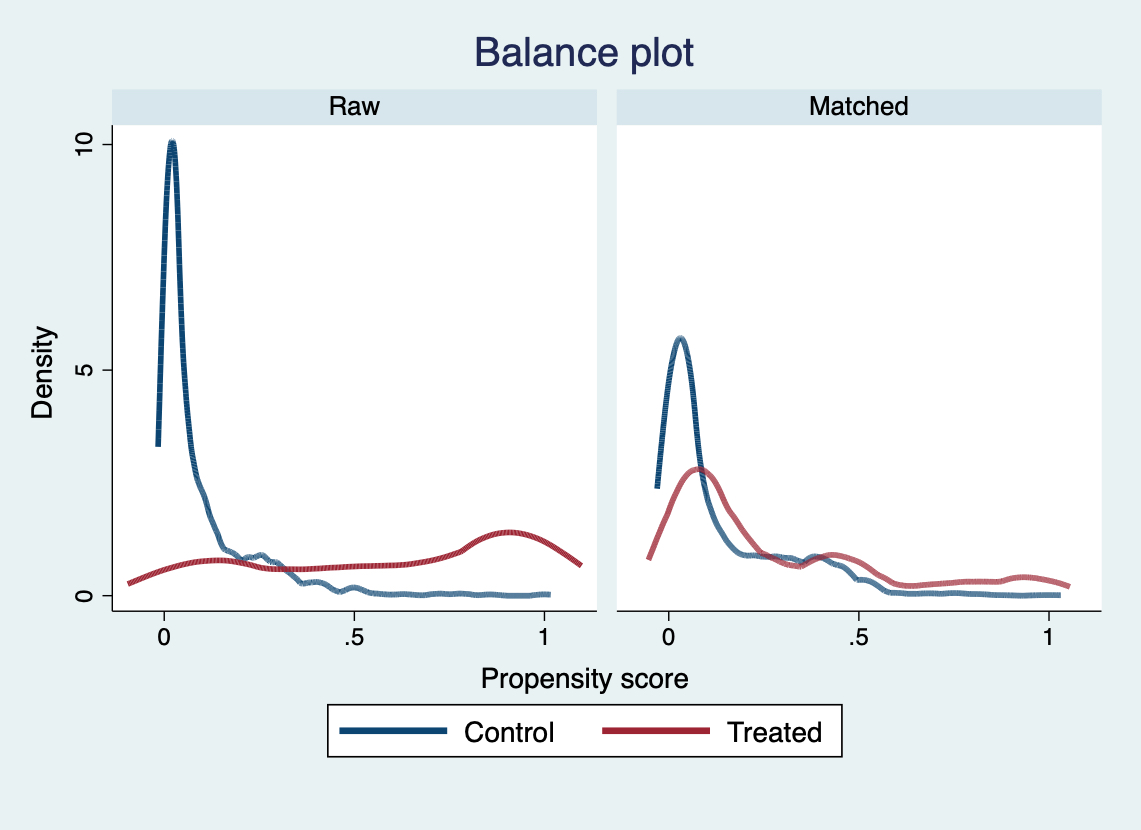
Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Coefficient estimates are reported using IV-regression models. In column (1), we eliminate the vectors of first job characteristics including economic activities, sectors of employment, incidence of work contract, and social security, as well as first occupation dummies. In column (2), we additionally control for years of entry in the labor market fixed effects. In columns (3) and (4), we cluster our regressions at the community level and by year of birth, respectively. In column (5), we aggregate occupational categories into agriculture, blue-collar occupations, and white-collar occupations. In column (6), we disaggregate occupational categories into 6 occupations: agriculture, blue-collar, low-skilled white-collar, technicians and associate professionals, legislators and managers, and professionals (ranked 1 to 6 respectively). In column (7), we eliminate high-skilled white-collar occupations at first job. In column (8), we focus on wage workers in 2010. In column (9), we restrict our analysis to wage workers at first job but also in the 2010 job.

**Figure A1*.* Oil prices versus aggregate indicators.**

*Notes.* Oil prices are inflation adjusted and expressed in $ per Barrel. Labor Force participation rate, Employment in agriculture, industry and services are from International Labor Organization, Key indicators of the Labor Market Database. GDP growth rates are from the World Bank National accounts data files.



**Figure A2*.* Balance plot of the propensity score.**

*Notes.* This figure reports the density of the propensity score between control (non-migrants) and treated units (return migrants). The left panel reports the density of the propensity score in the raw data, while the right panel reports the density of the propensity score after the matching using the nearest neighbor estimator.

|  |  |  |
| --- | --- | --- |
| **Table A1: Mean hourly and monthly wage by occupation** | | |
|  | (1) | (2) |
| Occupation | Hourly wage | Monthly wage |
| Agriculture | 4.636 | 762.954 |
|  | (0.317) | (50.052) |
| Low-skilled blue-collar | 6.867 | 1120.927 |
|  | (0.880) | (104.618) |
| High-skilled blue-collar | 7.401 | 1159.705 |
|  | (0.938) | (85.194) |
| Low-skilled white-collar | 8.776 | 1238.527 |
|  | (1.583) | (96.934) |
| High-skilled white-collar | 11.354 | 1990.873 |
|  | (0.620) | (96.893) |

*Notes.* Hourly and monthly wages in 2012 are reported in Egyptian Pounds, by occupation. Standard errors are reported between brackets.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table A2: Robustness checks to clustering, first stage regressions for the 1960s cohort** | | | |
| **Panel A: Community level clustering** | | | |
|  | (1) | (2) | (3) |
| VARIABLES | Return migrant | Return migrant | Return migrant |
|  |  |  |  |
| Oil price at age 25 | 0.024\*\*\* |  |  |
|  | [0.001] |  |  |
| Oil price at age 26 |  | 0.029\*\*\* |  |
|  |  | [0.000] |  |
| Oil price at age 27 |  |  | 0.029\*\*\* |
|  |  |  | [0.000] |
|  |  |  |  |
| Observations | 1,744 | 1,744 | 1,744 |
| **Panel B: Year of birth clustering** | | | |
|  |  |  |  |
| Oil price at age 25 | 0.024\*\*\* |  |  |
|  | [0.003] |  |  |
| Oil price at age 26 |  | 0.029\*\*\* |  |
|  |  | [0.002] |  |
| Oil price at age 27 |  |  | 0.029\*\*\* |
|  |  |  | [0.001] |
|  |  |  |  |
| Observations | 1,744 | 1,744 | 1,744 |
| Individual controls | YES | YES | YES |
| First job characteristics | YES | YES | YES |
| First occupation | YES | YES | YES |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Coefficient estimates for first stage IV-regressions are reported. In Panel A, we cluster our regressions at the community level. In Panel B, we cluster our regressions by year of birth (Panel B). We use the inflation-adjusted oil prices when the individual was 26 years old (the mean age at migration in our estimation sample). For robustness, we also tried to match the oil prices at age 25 and age 27.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table A3: Covariate balance before and after the matching** | | | | | | | | |
|  | | (1) | (2) | (3) | (4) | | (5) | (6) | |
|  | | **Before matching** | | | | **After matching** | | | |
|  | | Untreated | Treated | Difference | Untreated | | Treated | Difference | |
| VARIABLES | | Mean | Mean | Mean | | Mean |
| ***Individual characteristics*** | |  |  |  |  | |  |  | |
| Age at first job | | 17.744 | 15.375 | 2.369\*\*\* | 17.378 | | 15.372 | 2.006\*\*\* | |
| Secondary or less education | | 0.763 | 0.896 | -0.134\*\*\* | 0.883 | | 0.895 | -0.012 | |
| Above secondary education | | 0.237 | 0.104 | 0.134\*\*\* | 0.117 | | 0.105 | 0.012 | |
| Rural at birth | | 0.520 | 0.665 | -0.145\*\*\* | 0.631 | | 0.665 | -0.034 | |
| Above intermediate parental education | | 0.024 | 0.006 | 0.018\*\* | 0.009 | | 0.006 | 0.003 | |
|  | |  |  |  |  | |  |  | |
| ***First job characteristics*** | |  |  |  |  | |  |  | |
| *Economic activity* | |  |  |  |  | |  |  | |
| Agriculture, Forestry, Fishing | | 0.309 | 0.433 | -0.124\*\*\* | 0.372 | | 0.434 | -0.062 | |
| Manufacturing, Mining, Quarrying | | 0.148 | 0.116 | 0.032 | 0.12 | | 0.114 | 0.006 | |
| Construction | | 0.119 | 0.22 | -0.101\*\*\* | 0.231 | | 0.218 | 0.012 | |
| Wholesale, retail trade, transportation and other activities | | 0.219 | 0.128 | 0.091\*\*\* | 0.145 | | 0.129 | 0.015 | |
| Professional, scientific and administrative activities | | 0.018 | 0.027 | -0.01 | 0.031 | | 0.028 | 0.003 | |
| Other activities | | 0.189 | 0.076 | 0.112\*\*\* | 0.102 | | 0.077 | 0.025 | |
|  |  |  |  |  |  | |  |  | |
| *Sector of employment* | |  |  |  |  | |  |  | |
| Public | | 0.220 | 0.098 | 0.122\*\*\* | 0.129 | | 0.098 | 0.031 | |
| Private | | 0.780 | 0.902 | -0.122\*\*\* | 0.871 | | 0.902 | -0.031 | |
|  |  |  |  |  |  | |  |  | |
| *Incidence of work contract and social security* | |  |  |  |  | |  |  | |
| Work contract | | 0.256 | 0.098 | 0.159\*\*\* | 0.145 | | 0.098 | 0.046\* | |
| Social security | | 0.265 | 0.079 | 0.186\*\*\* | 0.111 | | 0.08 | 0.031 | |
|  |  |  |  |  |  | |  |  | |
| *First job occupation* | |  |  |  |  | |  |  | |
| Agriculture | | 0.306 | 0.43 | -0.124\*\*\* | 0.375 | | 0.431 | -0.055 | |
| Low-skilled blue-collar | | 0.122 | 0.067 | 0.055\*\*\* | 0.083 | | 0.068 | 0.015 | |
| High-skilled blue-collar | | 0.209 | 0.326 | -0.117\*\*\* | 0.311 | | 0.323 | -0.012 | |
| Low-skilled white-collar | | 0.116 | 0.079 | 0.037\* | 0.117 | | 0.08 | 0.037 | |
| High-skilled white-collar | | 0.247 | 0.098 | 0.150\*\*\* | 0.114 | | 0.098 | 0.015 | |
|  |  |  |  |  |  | |  |  | |
| Observations | | 1,426 | 328 |  | 325 | | 325 |  | |

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* In columns (1) and (2), we report the mean of all variables used in the Propensity Score Matching model to predict the propensity score using the nearest neighbor estimator for the full sample of untreated individuals (stayers) and the full sample of treated individuals (returnees), before the matching. Column (3) is a t-test for whether the difference in means between the two groups is statistically significant before the matching. In columns (4) and (5), we report the mean of all variables used in the Propensity Score Matching model to predict the propensity score using the nearest neighbor estimator for the matched sample of untreated individuals (stayers) and the matched sample of treated individuals (returnees), after the matching. Column (6) is a t-test for whether the difference in means between the two groups is statistically significant after the matching.

|  |  |  |
| --- | --- | --- |
| **Table A4: Estimating the effect of return migration on labor force participation for the 1960s cohort** | | |
|  | (1) | (2) |
|  | Linear probability model | IV-Regression |
| VARIABLES | Labor force participation | Labor force participation |
|  |  |  |
| Return migrant | -0.005 | -0.005 |
|  | (0.008) | (0.008) |
|  |  |  |
| Observations | 1,796 | 1,796 |
| R-squared | 0.030 | 0.030 |
| Individual controls | YES | YES |
| First job characteristics | YES | YES |
| First occupation | YES | YES |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Coefficient estimates are reported for linear probability and IV regression models. The dependent variable is a dummy variable indicator for labor force participation in primary job (reference 3 months).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table A5: Internal mobility matrices for stayers and returnees in the 1960s cohort** | | | | | | | |
|  | Current geographical region | | | | | | | |
| Geographical region at birth | Cairo | Alexandria and Canal cities | Urban Lower Egypt | Urban Upper Egypt | Rural Lower Egypt | Rural Upper Egypt | Total | | |
| **Panel A: Stayers (N=1,416)** | | | | | | | |
| Cairo | 11.370 | 0.282 | 0.071 | 0.141 | 0.212 | 0.212 | 12.288 | | |
| Alexandria and Canal cities | 0.141 | 7.627 | 0.071 | 0.000 | 0.212 | 0.000 | 8.051 | | |
| Urban Lower Egypt | 0.071 | 0.212 | 10.099 | 0.071 | 0.424 | 0.000 | 10.876 | | |
| Urban Upper Egypt | 0.565 | 0.353 | 0.141 | 15.325 | 0.071 | 0.353 | 16.808 | | |
| Rural Lower Egypt | 0.282 | 0.494 | 0.353 | 0.000 | 25.706 | 0.000 | 26.836 | | |
| Rural Upper Egypt | 0.636 | 0.212 | 0.141 | 0.706 | 0.353 | 23.093 | 25.141 | | |
| Total | 13.065 | 9.181 | 10.876 | 16.243 | 26.977 | 23.658 | 100.000 | | |
| **Panel B: Returnees (N=328)** | | | | | | | |
| Cairo | 6.098 | 0.000 | 0.000 | 0.000 | 0.305 | 0.000 | 6.402 | | |
| Alexandria and Canal cities | 0.000 | 2.744 | 0.305 | 0.000 | 0.305 | 0.000 | 3.354 | | |
| Urban Lower Egypt | 0.305 | 0.610 | 12.805 | 0.000 | 0.610 | 0.000 | 14.329 | | |
| Urban Upper Egypt | 0.000 | 0.610 | 0.000 | 8.537 | 0.000 | 0.305 | 9.451 | | |
| Rural Lower Egypt | 0.000 | 0.000 | 1.220 | 0.000 | 36.280 | 0.305 | 37.805 | | |
| Rural Upper Egypt | 0.305 | 0.000 | 0.305 | 0.610 | 0.305 | 27.134 | 28.659 | | |
| Total | 6.707 | 3.963 | 14.634 | 9.146 | 37.805 | 27.744 | 100.000 | | |

*Notes.* The table represents internal mobility matrices between the geographical region at birth and the geographical region in 2012. The diagonal cells represent the percentage of individuals who stayed in the same geographical region between the two time periods. The cells above and below the diagonal represent the percentage of individuals who moved to a different geographical region compared to their geographical region at birth.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table A6: Analyzing repeat migration using the 2018 survey** | | | | |
| **Panel A: Attrition between 2012 and 2018** | | | | |
|  | **Full sample** | | **1960s cohort** | |
|  | Freq. | Percent | Freq. | Percent |
| In 2012 only | 10,033 | 20.400 | 44 | 13.410 |
| In 2012 and 2018 | 39,153 | 79.600 | 284 | 86.590 |
| Total | 49,186 | 100.000 | 328 | 100.000 |
|  |  |  |  |  |
| **Panel B: Individual result from 2012 to 2018** | | | | |
|  | Freq. | Percent | Freq. | Percent |
| In original household | 34,325 | 69.790 | 280 | 85.370 |
| Split and found | 4,828 | 9.820 | 4 | 1.220 |
| Split and not found | 1,016 | 2.060 | 0 | 0.000 |
| Died | 1,743 | 3.540 | 12 | 3.660 |
| Emigrated | 763 | 1.550 | 3 | 0.910 |
| Moved to group housing | 122 | 0.250 | 0 | 0.000 |
| Household refused | 767 | 1.560 | 6 | 1.830 |
| Household not completed | 1,017 | 2.070 | 7 | 2.130 |
| Household not located | 4,605 | 9.360 | 16 | 4.880 |
| Total | 49,186 | 100.000 | 328 | 100.000 |
|  |  |  |  |  |

*Notes.* This table provides an analysis of repeat migration using data from the 2018 ELMPS. The entire 2012 sample is tracked into the 2018 survey. Panel A reports attrition between 2012 and 2018 for the full sample and for the 1960s cohort. Panel B provides individual result from 2012 and 2018. It provides information on whether the individual was retrieved in the original household or in split households. It also provides information on whether: the individual split to form a new household that was not found, the individual died, emigrated, moved to group housing, belongs to a household that either refused to answer the questionnaire, did not complete the questionnaire or was not located.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table A7: Comparing the 2010 occupations of returnees interviewed in 2018**  **versus those not interviewed in 2018** | | | | | |
|  | **Interviewed in 2018** | | **Not interviewed in 2018** | |  |
|  | (1) | (2) | (3) | (4) | (5) |
| VARIABLES | Mean | St. Dev. | Mean | St. Dev. | Difference |
|  |  |  |  |  |
| Agriculture | 0.250 | 0.434 | 0.159 | 0.370 | 0.091 |
| Low-skilled blue collar | 0.176 | 0.382 | 0.136 | 0.347 | 0.040 |
| High-skilled blue collar | 0.176 | 0.382 | 0.227 | 0.424 | -0.051 |
| Low-skilled white collar | 0.092 | 0.289 | 0.114 | 0.321 | -0.022 |
| High-skilled white collar | 0.306 | 0.462 | 0.364 | 0.487 | -0.057 |
|  |  |  |  |  |  |
| Observations | 284 | | 44 | |  |

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* This table presents the 2010 occupational distribution of returnees in the 1960s cohort. The table compares the occupational distribution of returnees who were successfully interviewed in the year 2018 in columns (1) and (2), versus those who were not interviewed in 2018 in columns (3) and (4). Column (5) reports the difference between the means reported in columns (1) and (3) as well as a t-test for whether the difference in means between the two groups is statistically significant.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table A8: Estimating the effect of return migration on occupational mobility for the 1950s cohort** | | | | |
|  | (1) | (2) | (3) | (4) |
|  | Linear Probability Model | IV-Regression | Linear Probability Model | IV-Regression |
| VARIABLES | Upward mobility | Upward mobility | Upward mobility | Upward mobility |
|  |  |  |  |  |
| Return migrant | 0.172\*\*\* | 0.118\*\* | 0.163\*\*\* | 0.110\*\* |
|  | (0.047) | (0.055) | (0.045) | (0.054) |
|  |  |  |  |  |
| Observations | 972 | 972 | 972 | 972 |
| R-squared | 0.165 | 0.164 | 0.221 | 0.220 |
| Individual controls | YES | YES | YES | YES |
| First job characteristics | YES | YES | YES | YES |
| First occupation | NO | NO | YES | YES |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Coefficient estimates are reported for linear probability and IV regression models.

|  |  |  |  |
| --- | --- | --- | --- |
| **Table A9: Difference-in-Differences Approach and Propensity Score Matching combined with Difference-in-Differences, for the 1950s cohort** | | | |
| **Panel A: Propensity score matching combined with Difference-in-Differences** | | | |
| **Sample of Returnees=160, Sample of Stayers=160** | | | |
|  | *Before the treatment* | *After the treatment* | *Difference* |
|  | *(t=0)* | *(t=1)* |
| *Returnees* | 2.550 | 3.237 | 0.688\*\*\* |
| *(Treatment group)* | (0.133) | (0.132) | (0.112) |
|  |  |  |  |
| *Stayers* | 3.500 | 3.731 | 0.231\*\*\* |
| *(Control group)* | (0.133) | (0.123) | (0.066) |
|  |  |  |  |
| *Difference* | -0.950\*\*\* | -0.494\*\*\* | 0.456\*\* |
| (0.170) | (0.169) | (0.208) |
| **Panel B: Propensity score matching combined with Difference-in-Differences, Matching on the first occupation** | | | |
| **Sample of Returnees=160, Sample of Stayers=160** | | | |
|  | *Before the treatment* | *After the treatment* | *Difference* |
|  | *(t=0)* | *(t=1)* |
| *Returnees* | 2.555 | 3.226 | 0.671\*\*\* |
| *(Treatment group)* | (0.131) | (0.130) | (0.109) |
|  |  |  |  |
| *Stayers* | 3.341 | 3.634 | 0.293\*\*\* |
| *(Control group)* | (0.128) | 0.120 | (0.075) |
|  |  |  |  |
| *Difference* | -0.787\*\*\* | -0.409\*\* | 0.378\* |
| (0.167) | (0.160) | (0.204) |

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

*Notes.* Panel A provides estimates from Propensity Score Matching, using the nearest neighbor estimator combined with Difference-in-Differences. Individuals are matched based on their age at first job, educational attainment, rural at birth, and first job characteristics, including economic activities, sector of employment, incidence of work contract, and social security. In Panel B, we additionally match individuals based on their first job occupation. In both Panel A and Panel B, the regressions include a dummy variable for each pair of matched stayer and returnee. Before the treatment refers to the first occupation and after the treatment refers to the occupation in 2010. The dependent variable is the individual’s occupation ranking. It takes values from 1 to 5 for the following categories respectively: agriculture, low-skilled blue-collar, high-skilled blue-collar, low-skilled white-collar and high-skilled white-collar.

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3. See Docquier and Rapoport (2012) for an excellent survey on the impact of emigration on the brain drain and brain gain in sending countries. [↑](#footnote-ref-3)
4. Bound, Khanna and Morales (2017) provide similar evidence from the United States, where increased high-skilled immigration led to an increase in the size of the information technology sector and firms’ profits. [↑](#footnote-ref-4)
5. See Wahba (2014) for a survey on return migration. [↑](#footnote-ref-5)
6. Williams and Baláž (2005) highlight the importance of examining “total human capital” as opposed to formal qualifications only. [↑](#footnote-ref-6)
7. See for example, Coniglio and Brzozowski (2018), who find that a skill mismatch during migration is often associated with a skill waste when migrants return home. Cobo, Giorguli, and Alba (2010) also examine the occupational mobility of Latin American returnees from the United States and find that the impact of international migration on occupational mobility is mediated by the characteristics of the home community, particularly its labor market. [↑](#footnote-ref-7)
8. The ETF survey interviewed 812 non-migrants and 1,000 return migrants, defined as adults aged 18 and above who had lived and worked abroad for at least 6 months and who had returned within the last 10 years preceding the survey. See Sabadie, Avato, Bardak, Panzica, and Popova (2010) for a description of the survey and questionnaire. [↑](#footnote-ref-8)
9. For example, Binzel and Assaad (2011), Wahba and Zenou (2012), Bertoli and Marchetta (2015), and Wahba (2015). [↑](#footnote-ref-9)
10. See Assaad and Krafft (2013) for data documentation. [↑](#footnote-ref-10)
11. The Egypt Labor Market Survey was first conducted in Egypt in 1988. However, the survey became a panel only starting from 1998. [↑](#footnote-ref-11)
12. It is important to note that all returnees in our data migrated for work purposes only. [↑](#footnote-ref-12)
13. The years considered for the 1960s birth cohort are from 1960 to 1969, inclusive. The choice of the 1960s cohort is guided by the desire to capture workers’ occupational mobility between their first and possibly last job. Relying on data from the ELMPS 2012 also allows us to observe individuals who were born in the 1960s, who migrated abroad, and eventually returned to Egypt. We also conducted several robustness checks, using 1950s cohort (see Section 5.4). All of our results were robust. [↑](#footnote-ref-13)
14. We compare the first occupation with the current occupation in 2010 instead of the occupation upon return to Egypt to have a comparable reference point for both return migrants and non-migrants (as well as in between non-migrants themselves). [↑](#footnote-ref-14)
15. It is important to note that we also exclude from our analysis all returnees who had their first job abroad. Throughout our analysis, we focus on returnees who had their first job in Egypt, since this allows us to control for pre-treatment first occupations. However, our results were also robust when we included individuals who had their first job abroad. [↑](#footnote-ref-15)
16. Since we rely on the ELMPS 2012, we use current job occupation in 2012 as individual’s occupation in 2010 if the individual did not witness any job status changes following the January 2011 Egyptian revolution. For individuals who witnessed job status changes in 2011 or after, we consider their employment status in 2010 and subsequently, we determine their job occupation in 2010. [↑](#footnote-ref-16)
17. Agriculture refers to skilled agricultural, forestry, and fishery work; low-skilled blue-collar refers to plant and machine operators, assemblers and elementary occupations; high-skilled blue-collar refers to craft and related trades; low-skilled white-collar refers to clerical support workers and service and sales workers; finally, high-skilled white-collar refers to managers, professionals, technicians, and associate professionals. Armed forces occupations are eliminated. [↑](#footnote-ref-17)
18. The monetary returns approach is fully consistent with the human capital approach to computing occupational rankings. We also computed occupational indices following the same methodology of Sicherman and Galor (1990) and Carletto and Kilic (2011) and found consistent occupational ranking. [↑](#footnote-ref-18)
19. Given that the percentage of stayers who had a high-skilled white-collar occupation at first job is higher than that of returnees (25% versus 10%) and since there is no potential upgrading for those who had a high-skilled white-collar occupation as their first job, in the robustness checks in Section 5.2 we eliminate individuals who had a high-skilled white-collar occupation at first job. Our results remain robust. [↑](#footnote-ref-19)
20. For robustness, we have also matched the oil prices with one year below and above the mean age at migration, and all results were robust. For the 1960s cohort, the mean age of migration is 26 years old, with a standard deviation of 5.1. [↑](#footnote-ref-20)
21. 99% of Egyptian migrants, in our estimation sample (1960s cohort), migrated to other Arab countries during their first migration episode. [↑](#footnote-ref-21)
22. We also find that the correlation between oil prices and men’s occupational distribution in Egypt in insignificant across all occupational categories, both in stocks and in flows, relying on data from 5 survey rounds of the ELMPS (1988, 1998, 2006, 2012 and 2018). [↑](#footnote-ref-22)
23. Data on labor force participation rate, employment in agriculture, industry, and services come from the International Labor Organization, Key indicators of the Labor Market Database. GDP growth rates come from the World Bank National accounts data files. The choice of the time period is dictated by data availability. [↑](#footnote-ref-23)
24. The community level corresponds to the smallest administrative unit in Egypt: *shyakha* in urban areas and villages in rural areas. [↑](#footnote-ref-24)
25. It is important to note that the dependent variable in the Difference-in-Differences matching model is equal to the occupational ranking for the five occupational categories. Thus, the results should be interpreted as how many steps return migrants are moving up the occupational ladder compared to stayers. Meanwhile, in the results reported using a linear probability and IV-regression models, the dependent variable is the probability of occupational upgrading between the first occupation and the 2010 occupation. [↑](#footnote-ref-25)
26. We aggregate all blue-collar occupations, since the mean hourly and monthly wage differences between these two categories are not large, as shown in Table A1 in the Online Appendix. We also disaggregate the high-skilled white-collar occupations to better observe the heterogeneity in occupational mobility for high-skilled white-collar occupations, since 39% of stayers and 31% of returnees in the 1960s cohort had high-skilled white-collar occupations in the 2010 job. [↑](#footnote-ref-26)
27. Returnees were also asked about the main use of their savings and we find that 76% of the returnees in our sample used their savings either to build or buy a house, buy agricultural land, or buy shares. Another 6% deposited their savings in banks. A related issue is that returnees could be more likely to drop out of the labor market earlier than stayers, perhaps since they have accumulated savings to see them through retirement. To address the issue, in Table A4 in the Online Appendix, we examine the impact of return migration on current labor force participation in 2012 for the 1960s cohort. Using linear probability and IV regression models, we do not find any significant effect of return migration experience on labor force participation. These results suggest that returnees in the 1960s cohort are not more likely to drop out of the labor force compared to stayers. [↑](#footnote-ref-27)
28. To compute the share of individuals who migrated internally, we sum the share of the cells below and above the diagonal in each panel. [↑](#footnote-ref-28)
29. In 2018, individuals were asked if they worked abroad for more than 6 months, as well as the year of their most recent migration and the year of their return. Among returnees in the 1960s cohort (328 returnees, out of which 284 were successfully interviewed in 2018), we only found two individuals who migrated again in 2011 and 2015 and they returned to Egypt in 2013 and 2016, respectively. [↑](#footnote-ref-29)
30. The years considered for the 1950s cohort are from the 1950 to 1959, inclusive. [↑](#footnote-ref-30)
31. For the 1950s cohort, the mean age of migration is 29 with a standard deviation of 2.4. [↑](#footnote-ref-31)
32. As further robustness checks, we also relied on labor market entrant cohorts rather than birth cohort. Based on the 1980s (and 1990s) labor market entrant cohorts, all our results hold. [↑](#footnote-ref-32)