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IFPRI Discussion Paper 01496

December 2015

Temporary and Permanent Migrant Selection

Theory and Evidence of Ability–Search Cost Dynamics

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ABSTRACT

The migrant selection literature concentrates primarily on spatial patterns. We integrate two workhorses of the labor literature, the Roy and search models, to illustrate the implications of migration duration for patterns of selection. Theory and empirics show that temporary migrants are intermediately selected on education, with weaker selection on cognitive ability. Longer migration episodes lead to stronger positive selection on both education and ability because the associated jobs involve finer employee-employer matching and offer greater returns to experience. Networks are more valuable for permanent migration, where search costs are higher. Labor market frictions explain observed complex network-skill interactions. When considering migrant selection, the economics literature has largely focused on patterns by area of origin. However, the duration of migration episodes–temporary versus permanent–is another important determinant of selection. We integrate two workhorses of the labor literature, the Roy model and a search model, to illustrate the implications of migration duration for patterns of self-selection. We provide theoretical and empirical evidence showing that, because short-term migration episodes have less scope for skill-based matching and greater need for screening, temporary migrants are more likely to display intermediate selection on education, with weaker selection on underlying cognitive ability. Longer term migration episodes, in contrast, allow for finer employee-employer matching and greater returns to experience, leading to stronger positive selection on both education and cognitive ability among permanent migrants. Networks are also found to be more valuable for permanent migration, where search costs tend to be higher. However, we also provide evidence of complex network-skill interactions, driven primarily by labor market frictions.

Keywords: conditional cash transfers, service delivery, decentralization, health

JEL Classification: J61, O15

ACKNOWLEDGMENTS

We thank Innovative Development Strategies Limited, Hak Lim Lee, Mekamu Kedir, Arshad Khurshid, Hina Nazli, and Sohail Malik for their assistance in the data collection and analysis, and Audrey Light, Pia Orrenius, and Caroline Theoharides for comments on previous versions of the manuscript.

This work was undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI). This paper has not gone through IFPRI's standard peer-review procedure. The opinions expressed here belong to the authors, and do not necessarily reflect those of PIM, IFPRI, or CGIAR. Any comments or suggestions are welcome; the authors may be contacted at chen.1276@osu.edu (Joyce Chen), k.kosec@cgiar.org (Katrina Kosec), or v.mueller@cgiar.org (Valerie Mueller).

1. INTRODUCTION

Trade—the movement of goods and services—has long been central to economic development, both in theory and in practice. But as the geographic mobility of workers continues to rise, *migration*—the movement of individuals and families—will be equally central to economic development. Remittances now far exceed official aid flows (Ratha et al. 2014), and the skill composition of migrants has increasingly greater consequences for destination markets (Card 1990; Borjas 2005; Card 2005; Borjas 2006; Ottaviano and Peri 2012). But, for migration unlike for trade, individuals must move with their *goods*, making the migration decision much more complex. Therefore, to better understand the impact of migration on both spatial and economic inequality, we must consider more deeply the migration decision itself.

The extant literature still largely fails to make substantive distinctions among migrants, despite drastically varied motives and experiences. In this paper, we take an initial step toward modeling heterogeneity among migrants, even those originating from the same area in the same time period, by focusing on the duration of migration episodes. We consider two types of migrants: temporary migrants, who tend to make short trips and then return to the area of origin, and permanent migrants, who tend to move over longer distances with no intention to return. Since short-term migration is typically motivated by transitory market fluctuations, the characteristics of short-term migrants will vary more with local economic conditions and business cycles. Their investment decisions, including those concerning human capital, will be based on the returns in local—rather than distant—labor markets (Dustmann 1993), and their households may be inclined to substitute human capital for social capital investments (McKenzie and Rapoport 2010). In contrast, characteristics of long-term migrants are more likely to be stable over time, shifting only when the underlying market structure changes. The gains to migration will primarily accrue at the destination, rather than returning to the area of origin. Because gains and search costs are amplified when migration is long term, there is a greater role for complementarities between worker ability and networks (Montgomery 1991; Loury 2006; Beaman and Magruder 2012).

In this paper, we describe patterns of selection into temporary and permanent migration. The simultaneity of migration, education, and other investment decisions creates a stark trade-off between a comprehensive, more descriptive assessment of self-selection and a narrowly focused identification of a specific causal relationship. We opt for the former because the characteristics of migrants are the principal determinant of the effects of migration on both sending and receiving areas. In contrast, identifying the underlying causes of selection would be more relevant for understanding the consequences of, for example, education policy on migration decisions.

We use data from a unique panel survey of rural households in Pakistan spanning 22 years (1991–2013) to study the drivers of migration during this time period. Our survey offers an array of detailed information on worker attributes, including education, cognitive ability (digit span and ravens test scores), and physical ability (height). To account for differences in search costs, we incorporate demographic and wealth information from 1991 to avoid simultaneity bias. We also include a measure of migrant networks, based on the movement of all respondents in an individual's community of origin (but not in the individual's household) since 1991. Because migration by network members is not contemporaneous, this strategy helps alleviate concerns about general equilibrium effects while still providing a good characterization of network size and scope. Since networks affect the costs *and* benefits of migration, we include a comprehensive set of interaction terms between migrant networks, education, and ability.

To formalize the differences between permanent and temporary migration, we embed a classic Roy (1951) model with heterogeneous moving costs, as in (Chiquiar and Hanson 2005; McKenzie and Rapoport 2010; Orrenius and Zavodny 2005), into a standard search model (Lippman and McCall 1976). Individuals choose between migration opportunities with either a permanent (lifetime) wage offer or a temporary (single-period) wage offer. The difference in the duration of these opportunities implies important distinctions not only in the decision process but also in patterns of self-selection, as well as in the data required to fully characterize migration decisions. Long-term employment affords greater opportunity for employer-employee matching and returns to experience, but these opportunities also require a more costly search process. Furthermore, while decisions about short-term moves can be adequately characterized by a static per-period problem, decisions about long-term moves are characterized by an optimal stopping problem. This fact intimates that recent (for example, those from the previous five years) migration histories may not adequately characterize individual migration choices. Finally, combining temporary and permanent migrants, and conflating the selection processes for the two types of moves, may be problematic if the composition of temporary versus permanent migrants is changing over time or is responsive to changing economic conditions.

Our empirical findings reveal positive selection on cognitive ability for both permanent and temporary migrants, driven by individuals with dense migrant networks. With regard to schooling, having a tertiary education increases the likelihood of permanent migration, while having a secondary education increases the likelihood of temporary migration, but only for those with weak migrant networks. Consistent with the model, these effects are stronger for permanent migrants, given the greater scope for employer-employee matching and returns to experience. Similarly, networks provide greater assistance for permanent migration, where search costs tend to be higher. But in the presence of moderate to dense networks, workers with more education are actually less likely to move overall, indicating that networks both draw high ability types and dissuade the highly educated. Taken together, these findings suggest that although networks can reduce search costs, particularly for high-ability workers, there are limits to how much they can help. Using an alternative data source (the Pakistan Labor Force Surveys), we show that our findings on education are consistent with a scenario in which networks alert highly educated workers of a low elasticity of demand for skilled labor at destinations, rather than a story of competition within thin markets (Calvo-Armengol 2004).

The remainder of the paper is organized as follows: Section 2 presents our theoretical framework, describing the choice between migrating permanently, migrating temporarily, or remaining at the area of origin. Section 3 describes our dataset, and Section 4 outlines our empirical approach. Section 5 presents our main results and robustness checks. Finally, Section 6 concludes.

2. THEORETICAL FRAMEWORK

A potential migrant faces a number of destination choices with different combinations of wages, search costs, and moving costs. Conceptually, we often narrow the decision process to a binary choice of whether to take the single best migration option or not. Yet it is becoming increasingly clear that migration options, even in developing countries, are much more heterogeneous and complex than such a simplified framework can explain. In this section, we lay out a basic search model to illustrate the key differences between permanent and temporary migration. We then embed features of a classic Roy (1951) model to consider how patterns of self-selection may differ with the duration of migration.

Search with Permanent and Temporary Opportunities

Consider two different types of migration that can be, and often are, employed by different individuals in the same period or by the same individual in different periods.[1] The first involves a *permanent* employment opportunity and, with it, a permanent change in residence. This type of migration often occurs over longer distances and requires more up-front investment. The second involves a *temporary* employment opportunity, necessitating a temporary change in residence but an eventual return to the area of origin. This type of migration typically occurs over shorter distances and is more frequently used as a short-term diversification or risk-coping mechanism, requiring relatively little upfront investment (Bryan, Chowdhury, and Mobarak 2014). Migration is no longer a binary choice; in each period, an individual considers both opportunities and selects the one that maximizes expected lifetime utility. Given differences between the two types of opportunities, we expect different patterns of selection as well.

To formalize this choice process, we employ a standard search model as in Lippman and McCall (1976). We assume an individual faces a fixed working life, with the length of this period, N, taken as given. Upon reaching adulthood, the individual receives a lifetime wage offer, w_0, in his or her *tehsil* of origin (home)—the home wage.[2] He or she also has employment opportunities outside of the home *tehsil*. A temporary employment opportunity with wage w_s is available in each period but for only a single period[3], akin to entering a spot market for labor at the destination. In this case, the individual observes a wage distribution for temporary employment opportunities with cumulative distribution function $G_t(\cdot)$. This distribution may vary from period to period,[4] with the mean of these temporary wage distributions drawn from a known distribution function, $\Gamma(\cdot)$. The individual must then incur a search cost, c_s, in order to acquire a specific wage draw, and once this cost has been incurred (that is, the individual has moved to the temporary labor market), the temporary wage offer must be accepted. These assumptions are motivated by the observation that migrants often observe labor market shocks at the destination and then engage in a search to secure a specific position and wage after migrating.

A permanent offer from outside the home *tehsil* can also be obtained in each period $t \in \{1, N\}$ by incurring a search cost, c_{pt}. Permanent employment provides a lifetime wage, w_p, drawn from a known distribution with cumulative distribution function $F(\cdot)$. In this case, search costs are incurred before the wage draw is received, consistent with the notion that permanent

[1] Destination choice is not considered explicitly here.

[2] A *tehsil* is an administrative unit (smaller than a district) in Pakistan. It encompasses multiple villages.

[3] The implications of the model do not hinge on the exact duration of temporary and permanent migration episodes. The key distinction is that permanent migration provides employment over a substantially longer period of time than does temporary migration.

[4] This specification allows us to incorporate wage shocks as a motive for temporary migration without specifying a stochastic process for wages. Without additional assumptions on risk preferences and the relative riskiness of wage distributions, (transitory) fluctuations in home and migrant wage distributions will have equivalent effects.

migrants typically identify a (set of) specific employment opportunities before migrating. We assume that the costs for permanent migration are increasing over time (that is, $dc_{pt}/dt > 0$), reflecting the notion that the search begins with destinations for which the individual has the best information but expands over time to include areas about which less is known.[5] In contrast, the search for temporary migration opportunities is generally concentrated among a small number of destinations that involve similar transportation and transaction costs, and for which the individual has comparable information. We further assume that once a permanent wage offer is accepted, search concludes, consistent with the existence of moving costs and liquidity constraints. Moving costs can be paid out of an initial asset endowment, but financing a second move is prohibitively expensive.[6] Temporary migration relocation may also be costly, but is much less expensive than a permanent move.

To identify the optimal migration strategies, we assume that the individual chooses the option in each period that maximizes expected discounted lifetime income, net of search costs. At time t, the individual may work in one of three jobs: home (0), permanent migration, (p), or temporary migration (s—for a single period). While in each job, he or she may also choose whether or not to search for another job. However, once a permanent job has been accepted, the search for permanent offers concludes. The individual may also recall (return to) any previous lifetime employment opportunity.

More formally, if the individual has not yet accepted a permanent wage offer, he or she considers the following choices, with the associated value functions:

1. Work in the home *tehsil* and do not search:
   $w_0 + \beta\varphi(w_p, t+1)$,

2. Work in the home *tehsil* and search:
   $w_0 - c_{pt} + \beta(1 - F(w_p))E\{\varphi(w, t+1)|w \geq w_p\} + \beta F(w_p)\varphi(w_p, t+1)$,

3. Accept a permanent wage offer:
   $w_p + \beta\vartheta(w_p, t+1)$,

4. Accept a temporary wage offer and do not search:
   $E[w_s] - c_s + \beta\varphi(w_p, t+1)$ or

5. Accept a temporary wage offer and search:
   $E[w_s] - c_s - c_{pt} + \beta(1 - F(w_p))E\{\varphi(w, t+1)|w \geq w_p\} + \beta F(w_p)\varphi(w_p, t+1)$

where β denotes the discount rate, w_p denotes the highest permanent wage offer to date, including w_0, $\varphi(w_p, t)$ denotes the maximum expected payoff to the individual given that he or she has received—but not accepted—a maximum wage offer w_p as of time t, and $\vartheta(w_p, t)$ denotes the expected lifetime utility given that a permanent wage offer w_p has been accepted at time t. If a permanent wage offer has already been accepted, then only options (3) and (4) are available,[7] and the value function for (4) becomes $E[w_s] - c_s + \beta\vartheta(w_p, t+1)$.

[5] While there may be some correlation with geographic distance, this assumption does not necessarily imply that earlier migrations will be over shorter distances. Individuals likely have a variety of network connections that provide information about a diverse set of destinations.

[6] This approach allows us to incorporate the implications of liquidity constraints without explicitly modeling savings decisions and specifying wealth as a state variable.

[7] Option (3) implies continuing to work in the permanent employment opportunity previously accepted.

By comparing the above value functions, we see that a temporary wage offer will be accepted when

$$E[w_s] - c_s > w_0 \text{ or } E[w_s] - c_s > w_p,$$

while a permanent wage offer will be accepted when

$$w_p > w_0 - c_{pt} + x_t,$$

where $x_t = \beta[\varphi(w_p, t+1) - \vartheta(w_p, t+1)] + \beta \int_{w_p}^{\infty} [\varphi(w, t+1) - \varphi(w_p, t+1)] f(w) dw$.

That is, a permanent wage offer will be accepted when the difference between the current wage offer and the home wage, net of search costs, exceeds the expected benefit of continued search, while a temporary offer will be accepted any time the expected earnings, net of search costs, exceed the current wage. The above two expressions highlight the key motivation for distinguishing temporary and permanent migration: the differing behavior of reservation wages over time. The reservation wage for temporary migration is constant over time. In each period, the individual simply evaluates earnings at home (or in another permanent job) relative to the distribution of earnings in the temporary employment market. There are no dynamic considerations involved in the decision because temporary migration is, by definition, a transitory event. In contrast, the search for permanent migration unfolds sequentially, and search costs increase over time as the search expands to include destinations for which the individual has less or worse information. A permanent migration decision is therefore an optimal stopping problem—rather than a single-shot choice—involving sequential search. Moreover, because permanent migration is very costly (irrevocable, in this case), timing is central to the decision process, since the option value of continued search decreases as the number of periods remaining in the individual's working life decreases (Lippman and McCall 1976).

One consequence of this distinction between permanent and temporary migration is the need to consider different reference periods. Because the reservation wage for temporary migration offers is time invariant, inferences based on migration activity in a single period of time (for instance, the last five years) will yield similar results irrespective of which "snapshot" in time is considered. In contrast, the reservation wage for permanent offers decreases over time because search costs increase over time and because, with a finite horizon, the expected value of continued search decreases over time. The likelihood of permanent migration therefore changes over time, and the age composition of the sample will affect both the number of migrants (within a given time frame) and, potentially, the patterns of self-selection that are observed. Thus, to accurately characterize permanent migration, data on lifetime migration histories is needed, particularly during the early adult years, when permanent migration is more likely.

Search costs also differ for permanent and temporary migration. Costs for temporary migration are paid after the migration decision is made, whereas those for permanent migration must be incurred before a wage draw is received. Consequently, higher search costs reduce the likelihood of temporary migration but may either increase or decrease the cumulative probability of permanent migration, conditional on T. Because search costs for permanent migration are sunk, once a wage draw is received, higher costs for continued search encourage acceptance of the current offer, increasing the likelihood of permanent migration, but also discourage continued search,[8]

[8] The search for a permanent wage offer will cease when the expected value of continued search no longer exceeds the cost. For offers $w \geq y_t$, the search will continue, where y_t is determined by equating the value functions for (1) and (2):

$$c_{pt} = \beta \int_{y_t}^{\infty} [\varphi(w, t+1) - \varphi(y_t, t+1)] f(w) dw.$$

increasing the likelihood that search concludes before an acceptable offer is obtained. The net effect, then, remains an empirical question.

To consider the effect of the wage distribution on migration decisions, consider alternative wage distributions $F'(\cdot)$ and $\Gamma'(\cdot)$ that first-order stochastically dominate $F(\cdot)$ and $\Gamma(\cdot)$. Ceteris paribus, the likelihood of receiving an acceptable wage offer will be higher under these alternative distributions for both permanent and temporary migration. But it is important to note that the wage distributions themselves may also reflect variation in search costs. However, observationally, we cannot distinguish between direct effects on the wage distribution (for example, individuals with more education face a higher wage distribution) versus effects of search costs operating via the wage distribution (for example, higher-quality information about migration opportunities eliminates the lower tail of the wage distribution, thereby increasing the mean, without reducing the fixed cost of acquiring information), because both alter the expected returns to migration. Thus, we continue to discuss "search costs" primarily as the costs associated with identifying migration opportunities while noting that any discussion of wage distributions and expected returns may implicitly involve search costs as well.

Self-selection

We next consider the effect of individual heterogeneity—ability, education, and access to migrant networks—on migration decisions. Note that this is not a causal model of the determinants of migration. We use this framework only to illustrate how different types of migration may result in different patterns of selection. Following Chiquiar and Hanson (2005), suppose wages and search costs are functions of individual characteristics as follows:

$$lnw_0 = \mu_0 + \delta_0(A,E,N),$$

$$lnw_p = \mu_p + \delta_p(A,E,N) + \epsilon_p \text{ with } \epsilon_p \sim F(\cdot), c_{pt} = \pi_{pt} - \theta_{\pi p}(A,E,N), \text{ and}$$

$$lnw_s = \mu_{st} + \delta_s(A,E,N) + \epsilon_{st} \text{ with } \epsilon_{st} \sim G_t(\cdot), c_s = \pi_s - \theta_{\pi s}(A,E,N).$$

δ is similar to a skill price but generalized to be a function of ability (A), education (E), and migrant networks (N). π represents the exogenous component of search costs (for instance, related to geographic remoteness), and θ is the component of search costs affected by migrant networks. Then, empirically, the effects of ability, education, and networks on migration depend on both the effect of the characteristic on the wage distribution (search costs) and the effect of the wage distribution (search costs) on the migration decision. This formulation is purposely very general because the lack of existing research comparing permanent and temporary migration provides no clear reasons a priori for specifying explicit relationships between individual characteristics and the two different types of migration. Nonetheless, we can provide some preliminary discussion about these relationships, which we will test in the empirical results section.

Consider first formal education. Education will affect the distributions of not only permanent and temporary wage offers but also the home wage offer. The relative returns to education in the migrant labor market(s) will then determine migration decisions. We may even observe a nonmonotonic relationship between education and migration if the relevant education-earnings profiles intersect. As in Chiquiar and Hanson (2005), this result depends not only on the effect of education on wages but also on the relationship between education and search costs. That is, if the returns to education are higher at the area of origin, we will observe strictly negative selection of migrants when $\pi = 0$. With only fixed migration costs, and provided the mean difference in wages offsets search costs, less educated individuals will relocate to destinations with

There may also be some individuals for which either search costs or the home wage are sufficiently high that search for another permanent offer never commences (analogous to the discouraged worker effect in models of unemployment).

lower returns to education. We can observe intermediate selection (migration of only workers in the middle of the education distribution) only when $\theta > 0$, creating the possibility that those in the middle of the education distribution have the greatest incentive to migrate (that is, because they have both relatively low migration costs and less to gain from higher returns to education at the area of origin).[9] Indeed, much of the observed relationship between education and migration will likely reflect the effect of education on search costs, given that our data include migration between a large set of locations in the same country, as well as both rural-urban and rural-rural migration, with no clear ordering of the returns to education between origin and destination points.

Migration will similarly be influenced by the relative returns to ability between migrant labor markets. However, formal education confers a credential that cognitive ability, on its own, does not, and this may be particularly useful when seeking work opportunities outside the origin *tehsil*. Comparing the effects of education and ability allows us to learn about the importance of screening in migrant labor markets. Put another way, if education is simply a proxy for ability then education should provide no additional return, conditional on ability. The relationship between ability and search costs conditional on education may also be less strong than that between education and search costs conditional on ability. For example, formal education may convey familiarity with the bureaucratic or administrative processes involved in migration, as well as enhanced knowledge of outside labor markets. It is difficult, empirically, to distinguish between the effects of ability on migration that come through its effects on search costs versus its effects on wage distributions. However, as mentioned above, intermediate selection of migrants would be indicative of a relationship between ability and search costs.

Finally, we consider the impact of migrant networks, which can be quite complex. Generally, access to information about migration opportunities and destination labor markets will increase the expected returns to migration, suggesting that networks may directly affect both search costs and wage distributions. Networks may affect fixed search costs, providing benefits across education and ability groups, particularly to those in more isolated markets. Conversely, networks may be selective, meaning either they are composed of individuals with certain characteristics or they support only individuals with certain characteristics. In both cases, the benefits of network access would tend to be concentrated among certain types of individuals, amplifying or dampening the effects of other characteristics, depending on the type of information or support the network provides. In this case, it is more difficult to discern whether network benefits operate through search costs or wage distributions—for example, referrals reduce the time spent locating employment opportunities but may also improve the set of opportunities accessible to the migrant.

Contrasting Permanent and Temporary Migration

From our model, we observe that differences in the duration of migration episodes generate important differences in patterns of migration. Short-term migration is a static decision involving only a simple comparison of current wage offers, whereas long-term migration involves dynamic considerations. This difference implies not only that age profiles will differ for each type of migration but also that lifetime migration histories should be examined because permanent moves are more likely to have occurred at younger ages. Moreover, permanent and temporary migrants are likely to differ in demographic composition (age), earnings potential at the destination (long-term versus short-term employment), and remittance behavior. These differences may help explain inconsistent findings in the existing literature regarding the effect of remittances on household investment and well-being.[10]

Additionally, the duration of migration episodes may affect patterns of selection. Searching

[9] For those with low levels of education, fixed migration costs are too high, while for those with the highest levels of education, higher returns to education at home make migration unattractive.

[10] Yang (2008) reviewed the bodies of literature that found opposing remittance impacts on household welfare.

for permanent positions is more costly than is searching for temporary positions. As a result, factors affecting search costs may have a proportionally larger effect on permanent migration. The relationships between education and migration, and between ability and migration, will also be stronger for employment opportunities that make greater use of either skills or screening. In the case of permanent migration, the search is more deliberate, so there is more scope for effectively matching skills with positions, suggesting a strong relationship between education, particularly higher education, and permanent migration. Conversely, the search in a spot market for temporary employment likely involves minimal matching, but employers may be more inclined to utilize observable skills such as education, particularly lower and middle levels, as a screening device. Ability is more difficult to observe than education; it may thus be a less effective screening mechanism for temporary employment, where employees are typically hired with minimal evaluation. However, these factors do not necessarily imply there is no role for ability in temporary migration. Provisional employment opportunities may also be more prevalent in a spot market, allowing (unproven) workers to demonstrate their ability on the job, whereas separation costs (for instance, unemployment benefits) may inhibit such arrangements for longer-term positions.

With regard to migrant networks, the information they provide is likely both more cost saving and more useful when a search is conducted over longer distances, both physical and social. For example, economic shocks—such as a construction boom—in potential markets for temporary migration may be easy to observe in comparison with the long-term returns to education/ability that would be relevant for permanent migration. Temporary migrants are also more likely to consider the same set of potential destinations repeatedly, whereas permanent migrants will search sequentially, over increasingly distant markets. Thus, we might expect networks to have a larger effect on permanent migration than on temporary migration. However, another important feature of networks is their capacity to provide referrals. This may involve either facilitating skill-based matching between employers and potential employees in long-term positions, or simply filling temporary labor shortages with network members, or both. With regard to referrals, we may also observe interesting interactions between migrant networks and education or ability, which will depend on the behavior of networks in assisting different types of workers in finding permanent versus temporary positions.

3. DATA

Our main source of data is a survey carried out in Pakistan during September 2013–July 2014 that tracked all individuals in a set of households last surveyed in 1991 as part of the International Food Policy Research Institute's (IFPRI's) Pakistan Panel Survey (PPS) (1986–1991).[11] We refer to this latest follow-up, 22 years later, as the Pakistan Panel Tracking Survey (PPTS). The PPTS survey team visited all 726 households surveyed in 1991, which we refer to as the PPS households. They are spread across five districts: Attock, Faisalabad, and Toba Tek Singh (in the Punjab province); Badin (in the Sindh province); and Lower Dir (in the Khyber Pakhtunkhwa, or KPK, province). Using original (that is, 1991) rosters of all PPS households, the survey team completed a tracking roster documenting all original household members' current whereabouts. Any original member of a PPS household who was alive and residing in-country at the time of the PPTS was eligible for tracking. Once PPS households were contacted and a tracking roster completed for each of them, a current household roster was constructed for each PPS household and each "split-off" household formed by an original PPS household member. We complement data from the 1991 PPS and the 2013–2014 PPTS with data from a tracking survey carried out in 2001 by the Pakistan Institute for Development Economics (PIDE 2001); Nayab and Arif (2012) describes this dataset. This survey team visited each of the original 726 PPS households and completed a tracking roster that noted whether each original PPS household member was present, not present but still considered a household member, or no longer a household member. For those who were no longer members, the survey recorded whether their new location was in Pakistan or abroad.

We study the permanent and temporary migration behavior between 1991 and 2013 of male original PPS household members aged 22–60 at the time of the PPTS. These individuals were alive but under age 38 in 1991, allowing us to focus on migration of young, working-age adults. Individuals who joined the PPS household after 1991 or who are members of split-off households are not in our sample. The final sample for analysis consists of 1,346 adult men at risk of migrating permanently during 1991–2013.

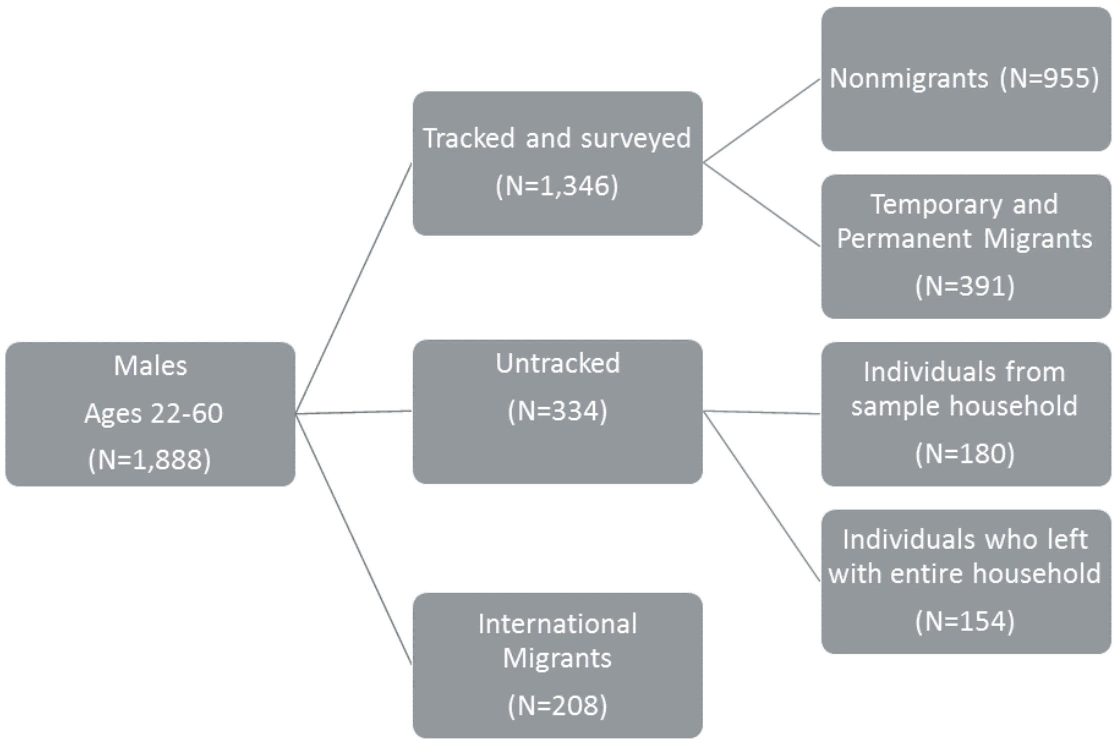
Attrition

Figure 3.1 illustrates our success rates in tracking male original members of PPS households who were aged 22–60 at the time of our 2013–2014 PPTS. Of 1,888 men, 208 were international migrants and thus ineligible for tracking. An additional 154 were members of households for which no original member could be traced. This represents a household attrition rate of 4 percent, which is comparable to that of other large panel surveys (Thomas, Frankenberg, and Smith 2001). Excluding these two groups, 180 of 1,526 individuals attrited from the survey between 1991 and 2013–2014, just under 12 percent. Tracking concluded prematurely in August 2014 due to security conditions in the field, which also prevented any tracking of international migrants.[12]

[11] The PPS was carried out in 14 rounds over a period of five years.

[12] Individuals were unwilling to answer calls from enumerators with unknown phone numbers, and worsening security conditions precluded revisiting the households to schedule a call to complete a short survey.

Figure 3.1 Pakistan Panel Tracking Survey 2013–2014



Source: IFPRI (2014).

Individual attrition is of particular concern in the context of a migration study because the majority of attritors are migrants as well. To gauge the severity of this problem, we report in Table A.1 6. the 1991 characteristics of tracked and untracked respondents. We find few significant differences across groups, except that untracked respondents originate from somewhat wealthier and better-educated households. In contrast, individuals who attrited along with their full households differ greatly from tracked respondents and are worse off overall. They are younger, and their households have less education and wealth, are larger in size, and have higher dependency ratios. These observable characteristics suggest that individuals attriting with their full households are motivated to migrate more by distress than as part of a forward-looking optimization strategy, distinguishing them from other types of migrants. In light of this observation, and given our model's focus, we omit this group from the analysis, with the caveat that our results cannot be generalized to the case of full household migration.

Based on reports from the household head, we can also determine whether an untracked migrant has moved permanently or temporarily. Of the 180 individuals that could not be tracked, 124 were permanent migrants (69 percent), 29 (16 percent) were temporary migrants, and 27 (15 percent) were located in the original 1991 *tehsil* but refused to respond to the survey. Attrition is largely from permanent migrants, and a larger portion of permanent migrants (46 percent, versus 11 percent for temporary migrants) could not be tracked. This finding is consistent with permanent migrants traveling longer distances, both geographic and social, and therefore being more difficult to locate. The tracking rate for temporary migrants is also higher because those who were reported as temporarily away in earlier survey rounds have returned and did not require special tracking in 2013–2014. In terms of observable characteristics, untracked permanent migrants are slightly younger and come from more educated households, compared to tracked permanent migrants. Untracked temporary migrants are younger and come from smaller, wealthier households when compared to tracked temporary migrants. Given these differences, we perform robustness tests for sample attrition.

Migration

Our primary interest lies in understanding what leads an individual to migrate, permanently or temporarily, versus not at all. However, since we lack complete data on migration histories, we focus on an individual's first move since 1991. Therefore we divide individuals in our sample into three mutually exclusive, exhaustive categories: those that never migrate, those whose first move was a temporary one (hereafter, temporary migrants), and those whose first move was a permanent one (hereafter, permanent migrants).[13] We define permanent migration as no longer being considered a member of the original PPS household at the time of the 2013–2014 PPTS. We further require a move to be out of the origin *tehsil* to count it as migration, to avoid capturing local marital moves. Permanent migration may have occurred any time during 1991–2013 but, by construction, can only occur once. We define temporary migration as an individuals being temporarily away—but still considered a PPS household member—at the time of any of our three visits: 1991, 2001, and 2013–2014.[14]

The requirement that temporary migrants still be considered members of the PPS household distinguishes them from permanent movers. As an additional safeguard, to ensure that we do not code a permanent migration episode as a temporary one, we further require that an individual who was temporarily away at one of these three points in time had not permanently left the PPS household at the time of a subsequent survey. Specifically, in the case of individuals temporarily away (but still considered household members) in 1991, we require that they still be household members at the time of the 2001 survey. In the case of individuals temporarily away (but still considered household members) in 2001, we require that they still be considered household members at the time of the 2013–2014 survey.[15] About 10.9 percent of our sample for analysis is coded as permanent migrants and 18.1 percent as temporary migrants.

Education and Ability

Labor market potential and search costs are functions of individual skill and ability. To capture skill, we include three categories of education: completed primary education, completed secondary education, and completed higher secondary or tertiary education, with no education or less than primary education as the reference category.[16] We also include a measure of ability that is independent of education: the Digit Span test score. We compute z-scores based on the number of correct responses to 16 forward and backward Digit Span questions. Respondents are provided a set of numbers and asked to repeat the same numbers in the same and opposite order. This tests an individual's attention, memory, and—for the backward Digit Span test—the higher-order

[13] Individuals may have a temporary and a permanent move; we focus on the first move. Because only original 1991 PPS households were surveyed in 2001, we cannot observe a temporary move after a permanent move.

[14] Our definition of temporary migration is not based on the number of months in the last year that the individual was temporarily away because we lack such information on total months away for one of these three points in time: 2001. We use only information on household membership and whether the individual is currently (at the time of the survey) away.

[15] Clearly, we cannot verify the return migration of household members reported as currently away in 2013-14. However, our results are robust to excluding this group of temporary migrants.

[16] Secondary education includes grades 9 and 10 while higher secondary education (also called college) includes grades 11 and 12. In Pakistan, the primary motivation for obtaining higher secondary education is that it is a requirement for getting into university (tertiary education)—though it may also open up new job opportunities that require a Higher Secondary (School) Certificate.

cognitive ability to invert the order of information.

The overall Digit Span z-score is our primary measure of cognitive ability, but we also examine the robustness of our results to several alternative measures, also converted into z-scores: Digit Span forward, Digit Span backward, standing height, and components of Raven's Progressive Matrices tests (Raven, Raven, and Court 2000). Height has been positively associated in other settings with measures of both cognitive and noncognitive abilities (Vogl 2014; Schick and Steckel 2015) and may visually signal this ability. Raven Test Scores measure abstract reasoning; individuals are shown a series of patterns (matrices) and are asked to select the missing element from a set of eight possibilities.

Community Networks and Search Costs

Access to community networks can reduce the costs of migration through the provision of housing, knowledge of labor market conditions, and referrals, among other factors (Carrington, Detragiache, and Vishwanath 1996; Munshi 2003; McKenzie and Rapoport 2007, 2010). Following Massey, Goldring, and Durand (1994) and McKenzie and Rapoport (2010), we measure an individual's community migration network using the share of all original PPS village members (excluding members of one's own household) who migrated during 1991–2013—whether permanently or temporarily. We include both male and female migrants because migrants of either gender—and individuals in their new households—may assist migrants. This formulation of networks helps to mitigate simultaneity bias because, although it focuses on migrants originating from the same village, it incorporates migration activities over a long time period. As a result, networks are less likely to be correlated with either local economic conditions in the area of origin at the time of migration or composition effects in the labor market driven by recent migration trends. We also examine the sensitivity of our findings to alternative network definitions.

We use distance of the PPS village to a primary (that is, paved and high-quality) road in 1994 to account for the effect of search costs on migrant selection (Survey of Pakistan 1994).[17] In selected cases where we lack village GPS coordinates, we assign to the village the centroid of its *tehsil*, computed from a map of *tehsil* boundaries (OCHA and PCO 2011) . Additionally, we control for the amount of nonland durable assets owned by the PPS household in 1991, which reflects the household's ability to finance search and moving costs.

[17]Although the Survey of Pakistan (1994) does not provide a clear definition of a primary road, it distinguishes primary roads from secondary and tertiary roads based on their type/quality (paved, gravel, or dirt), condition (good or bad), and drivability (all weather or only dry weather).

4. EMPIRICAL STRATEGY

Our main objective is to test how selection differs for permanent and temporary migrants. Given the limited empirical work on this topic, our model allows for flexible relationships between education, ability, networks, and migration. Migrant selection is modeled via a linear probability model[18] with separate regressions for permanent and temporary migration:

$$Y_{ihl} = \alpha + \beta_X X_{ih} + \beta_E E_i + \beta_A A_i + \beta_C C_l + \beta_N N_h + \gamma_l + \epsilon_{ihl}, \quad (1)$$

where Y_{ihl} is an indicator for whether individual i in household h migrated (temporarily or permanently) from village l during 1991–2013; X_{ih} is a vector of individual and household factors that affect the decision to migrate (age categorical variables; an indicator for having ever been married; and tercile categorical variables for the number of household members, number of child members, and value of durable assets in the associated 1991 PPS household); E is a vector of education level indicators; A is a measure of individual ability—our primary measure of interest being the Digit Span z-score; C is search costs, proxied by tercile categorical variables indicating the distance from location l to a primary road in 1994; and N captures the community migrant network, measured by tercile categorical variables for the share of all original PPS village members who migrated during 1991–2013. Given the cross-sectional nature of the analysis, we also include province fixed effects (γ).

To the extent possible, we mitigate endogeneity concerns by using values from 1991, before migration occurred. Including a direct measure of cognitive skill also helps to reduce ability bias for schooling. Still, we cannot purport to estimate *causal* effects of education and migrant networks, given the simultaneity of these decisions and migration. We would argue, however, that descriptive analysis is essential to both future research and policymaking. First, there is little to no empirical evidence on how permanent and temporary migrants differ and to what extent. Second, in order to understand how expanding opportunities for migration will affect the composition of migrant cohorts and the impact on destination economies, it is critical to fully understand descriptive patterns of selection.[19] Similarly, understanding selection patterns is essential to estimating the impact of migration on origin communities and households.[20] Our analysis thus provides an important starting point for deepening understanding of the migration decision and its impact on local economies.

Although we use the same specification for permanent and temporary migration in order to facilitate comparison, there are differences in the underlying relationships being estimated. As noted above, permanent migration is a sequential decision, while temporary migration can be represented by a static problem. Thus, for permanent migration, we look at the individual's entire migration history—that is, the cumulative probability that the individual has accepted a permanent migration opportunity by time T.[21] In contrast, for temporary migration, we look at

[18] Our findings are robust to the use of a logit specification (Table A.2).

[19] Estimating the causal effect of schooling on migration would, in contrast, be more relevant for considering the impact of a proposed education policy.

[20] Indeed, this line of research commonly includes this type of descriptive analysis of migrant selection in the form of a first-stage equation.

[21] This can be written as

$$\sum_1^{min\{D,T\}} \{[1 - F(w_0 - c_s - c_{pt} + x_t)] \prod_0^{t-1} F(w_0 - c_s - c_{pt} + x_t)\},$$

and $\sum_1^T 1 - [\Gamma(w_0 + c_s)]^t$

where D is the period in which the search concludes (search costs equal the option value of continued search), determined as follows:

the probability that an individual has accepted a temporary employment opportunity in one of three time periods—1991, 2001, or 2013–2014.[22] When we look at the Pakistani Labor Force Survey, we find approximately 2 percent of males aged 22–60 reported as "temporarily away" in each year, compared with 18 percent of our sample that has engaged in temporary migration in at least one of the three time periods. This comparison suggests that our measure does not substantially undercount temporary migrants, though we do miss temporary migration episodes in the intervening years. Since the temporary migration decision is essentially the same in each period, however, our results should not be affected by the choice of periods or by limiting our attention to only three periods. Nonetheless, we test this assumption more carefully below.

$c_{pD} = \beta \int_{w_p}^{\infty} [\varphi(w,t+1) - \varphi(w_p,t+1)] f(w) dw$.

[22]This can be written simply as $1-[\Gamma(w_0+c_s)]$. But with our focus on first moves, falling reservation wages for permanent migration reduce the likelihood, over time, that a temporary migration will occur before a permanent one. Thus, although the probability of temporary migration does not, in our model, vary with age, the likelihood of having a temporary migration *before* a permanent migration may decline with age because the increasing likelihood of permanent migration reduces the number of "eligible" individuals.

5. RESULTS

Basic Specification

Summary statistics are presented in Table 5.1. Permanent migrants are older than nonmigrants, and the opposite is true for temporary migrants. Both temporary and permanent migrants appear to have certain advantages for migration. They are, on average, closer to a primary road and have denser migrant networks relative to their nonmigrant counterparts. Both migrant types also have higher cognitive scores than nonmigrants, and a greater proportion of temporary migrants have completed secondary education or more. Among permanent migrants, a greater proportion have also completed education beyond secondary school, but the proportion completing secondary school is comparable to that of nonmigrants. Permanent migrants also come from households with greater asset wealth per capita, while the opposite is true for temporary migrants, though the latter come from larger households, on average.

Table 5.1 Summary statistics

Variable	Nonmigrant mean	Permanent migrant mean	Difference (p-value)	Temporary migrant mean	Difference (p-value)
Age 15–24	0.12	0.05	0.02	0.19	0.00
Age 25–34	0.29	0.3	0.65	0.29	0.95
Age 35–44	0.3	0.32	0.67	0.26	0.16
Age 45–54	0.24	0.24	0.84	0.22	0.56
Age 55–64	0.06	0.08	0.27	0.05	0.45
Incomplete primary education	0.34	0.28	0.13	0.21	0.00
Completed primary education but not	0.3	0.28	0.78	0.27	0.47
Completed secondary education	0.16	0.18	0.68	0.24	0.01
Completed higher than secondary education	0.2	0.26	0.09	0.28	0.01
Married (presently or in past)	0.81	0.82	0.67	0.76	0.09
1991 durable assets (1,000 rupees)	88.57	134.32	0.01	97.94	0.48
1991 HH size	12.18	11.93	0.65	13.16	0.03
1991 number of child HH members	5.47	5.00	0.17	5.77	0.30
Distance from primary road (km)	23.9	18.58	0.01	18.90	0.00
Raven z-score (overall)	-0.07	0.09	0.08	0.16	0.00
Raven z-score (A)	-0.05	0.18	0.01	0.21	0.00
Raven z-score (B)	-0.06	0.04	0.24	0.12	0.01
Raven z-score (D)	-0.06	-0.01	0.62	0.07	0.08
Digit Span z-score (overall)	-0.08	0.13	0.01	0.28	0.00
Digit Span z-score (forward)	-0.07	0.17	0.00	0.16	0.00
Digit Span z-score (backward)	-0.09	0.09	0.08	0.21	0.00
Height z-score	-0.04	0.14	0.04	0.20	0.00
Employed on own farm	0.39	0.18	0.00	0.31	0.02
Employed in wage labor	0.54	0.74	0.00	0.61	0.04
Self-employed in enterprise	0.05	0.09	0.03	0.05	0.70
Community networks, 1991	0.31	0.36	0.00	0.35	0.00
Community networks with above median Digit Span scores, 1991	0.13	0.16	0.00	0.14	0.03
Community networks with secondary or above completed education, 1991	0.09	0.11	0.00	0.11	0.00
Community networks with above median age, 1991	0.14	0.17	0.00	0.16	0.00
Province of 1991 village is Punjab	0.45	0.65	0.00	0.51	0.07
Province of 1991 village is KPK	0.25	0.20	0.17	0.33	0.02
Province of 1991 village is Sindh	0.3	0.15	0.00	0.16	0.00
N	955	148		243	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: HH= household; KPK = Khyber Pakhtunkhwa.

Table 5.2 provides ordinary least squares results from regressions of permanent (columns 1–4) and temporary (columns 5–8) migrant selection. We estimate four stepwise regressions, starting with the inclusion of indicators for the province of the household member's origin village and the individual's age and marital status (columns 1, 5). We then add individual education and cognitive ability (columns 2, 6). Next, we introduce the individual's 1991 PPS household demographics, wealth level, and distance to a primary road (columns 3, 7), and finally we add community migrant networks (columns 4, 8). The final column provides the difference in each estimated coefficient across temporary and permanent migrant selection equations, comparing columns 4 and 8. The p-value from a test for the statistical significance of this difference is presented in brackets below the difference.

The likelihood of permanent migration is increasing in age, consistent with the decreasing reservation wage in our model. Interestingly, the oldest group in our sample has the highest likelihood of permanent migration, and we see no evidence of leveling off, which would occur if the search for permanent wage offers ceased at some age below the upper bound of our sample (60). In contrast, we observe a flattening of the age profile for temporary migration because the increasing likelihood of permanent migration supersedes the (constant) likelihood of temporary migration.[23] These coefficients are stable across specifications and consistent with the raw sample means, suggesting minimal correlation between age and other regressors.

Our theoretical model allows both search costs and the returns to migration to vary with worker attributes. As a first pass, we enter education and ability linearly in the migrant selection equations. Cognitive ability positively affects both forms of migration; a 1 standard deviation increase in an individual's Digit Span z-score increases the likelihood of both permanent and temporary migration by 6.7 percentage points relative to sample means of 11 percent and 18 percent for permanent and temporary first movers, respectively. The similarity of the point estimates is striking although, proportionally, the effect is considerably larger for permanent migration. This is consistent with higher rewards for cognitive skills in long-term than in short-term employment opportunities (for example, due to employee-employer match quality, firm- or industry-specific human capital, and so on.). In contrast, education has a statistically insignificant and small impact on migration. This finding suggests that education is strongly correlated with innate cognitive ability—consistent with a standard ability-bias story—and likely other covariates as well (for instance, wealth, household composition). Together, these estimates suggest that conditional on innate cognitive ability, there is little to gain in migrant labor markets from formal education, at least in this context. This implication may indicate either low-quality schooling or limited demand for educational signaling and screening in migrant labor markets.

[23] Our estimated parameters likely reflect both age and cohort effects due to the cross-sectional nature of our data. The negative coefficients may be indicative of older cohorts in our sample facing weaker labor markets for temporary migration (that is, unfavorable wage distributions). The differences in the age parameters, however, appear robust, albeit less precise, to focusing on the sample of people at most risk of moving permanently (22- to 4- year olds in our sample). Results available upon request.

Table 5.2 Migrant selection, including attritors

Variable	Permanent migration				Temporary migration				Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)-(4)
KPK province (1991)	-0.074	-0.178	-0.188	-0.140	0.022	-0.109	-0.107	-0.053	0.086
	(0.035)**	(0.068)**	(0.059)***	(0.066)**	(0.047)	(0.056)*	(0.088)	(0.087)	[0.427]
Sindh province (1991)	-0.113	-0.091	-0.012	0.016	-0.106	-0.091	-0.111	-0.078	-0.094
	(0.035)***	(0.038)**	(0.046)	(0.030)	(0.043)**	(0.045)**	(0.052)**	(0.039)*	[0.015]
Age 25–34		0.092	0.093	0.088		-0.070	-0.069	-0.074	-0.162
		(0.037)**	(0.037)**	(0.038)**		(0.046)	(0.046)	(0.047)	[0.008]
Age 35–44		0.090	0.088	0.084		-0.097	-0.094	-0.096	-0.180
		(0.033)***	(0.032)***	(0.032)**		(0.050)*	(0.050)*	(0.051)*	[0.001]
Age 45–54		0.094	0.087	0.081		-0.085	-0.086	-0.089	-0.171
		(0.035)**	(0.032)**	(0.032)**		(0.057)	(0.057)	(0.057)	[0.009]
Age 55–64		0.147	0.133	0.133		-0.103	-0.105	-0.104	-0.237
		(0.060)**	(0.061)**	(0.061)**		(0.050)**	(0.053)*	(0.054)*	[0.003]
Ever married		-0.010	-0.008	-0.006		0.014	0.010	0.010	0.016
		(0.029)	(0.029)	(0.029)		(0.036)	(0.035)	(0.035)	[0.726]
1991 HH size, tercile two		0.011	0.002	0.007		0.059	0.053	0.058	0.051
		(0.035)	(0.036)	(0.034)		(0.045)	(0.049)	(0.049)	[0.217]
1991 HH size, tercile three		0.046	0.033	0.035		0.129	0.121	0.125	0.090
		(0.056)	(0.059)	(0.059)		(0.057)**	(0.058)**	(0.058)**	[0.135]
1991 number of children in HH, tercile two		-0.025	-0.013	-0.015		0.005	0.010	0.012	0.027
		(0.041)	(0.044)	(0.043)		(0.041)	(0.040)	(0.041)	[0.513]
1991 number of children in HH, tercile three		-0.044	-0.041	-0.038		-0.075	-0.072	-0.071	-0.033
		(0.063)	(0.065)	(0.065)		(0.057)	(0.057)	(0.058)	[0.585]
Completed primary education		-0.021	-0.027	-0.031		-0.002	-0.004	-0.012	0.020
		(0.025)	(0.024)	(0.025)		(0.028)	(0.027)	(0.028)	[0.616]
Completed secondary education		-0.019	-0.029	-0.028		0.045	0.044	0.045	0.072
		(0.031)	(0.031)	(0.031)		(0.033)	(0.030)	(0.030)	[0.110]
Completed higher than secondary education		-0.003	-0.015	-0.016		0.006	0.003	-0.003	0.013
		(0.039)	(0.036)	(0.037)		(0.034)	(0.031)	(0.030)	[0.785]

Table 5.2 Continued

Variable	Permanent migration				Temporary migration				Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)-(4)
Digit Span z-score		0.072	0.069	0.067		0.069	0.068	0.067	-0.000
		(0.037)*	(0.037)*	(0.037)*		(0.021)***	(0.020)***	(0.019)***	[0.997]
1991 HH assets, tercile two			0.023	0.023			-0.031	-0.030	-0.052
			(0.034)	(0.033)			(0.031)	(0.031)	[0.172]
1991 HH assets, tercile three			0.047	0.043			0.050	0.043	-0.000
			(0.043)	(0.045)			(0.041)	(0.040)	[0.996]
Dist. to primary road, tercile two			0.021	0.050			-0.004	0.031	-0.020
			(0.050)	(0.048)			(0.082)	(0.078)	[0.829]
Dist. to primary road, tercile three			-0.088	-0.048			0.042	0.094	0.142
			(0.041)**	(0.037)			(0.073)	(0.073)	[0.049]
Migrant networks, tercile two				0.017				0.033	0.016
				(0.039)				(0.051)	[0.694]
Migrant networks, tercile three				0.082				0.106	0.023
				(0.042)*				(0.046)**	[0.670]
Constant	0.184	0.145	0.139	0.067	0.226	0.276	0.267	0.174	
	(0.028)***	(0.047)***	(0.042)***	(0.052)	(0.032)***	(0.052)***	(0.079)***	(0.089)*	
R^2	0.02	0.05	0.06	0.06	0.02	0.05	0.06	0.06	
N	1,103	1,103	1,103	1,103	1,198	1,198	1,198	1,198	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: HH = household; KPK = Khyber Pakhtunkhwa. Standard errors in parentheses. * p < 0.1 ** p < 0.05; *** p < 0.01. P-values in brackets for statistical difference in coefficient estimates across models.

Next, we examine how search costs and the ability to finance them affect migrant selection, drawing on the parameter estimates of distance to a primary road, initial household wealth, demographics, and networks. First, residing in a location very far from a primary road (in the third tercile) is associated with a statistically significantly lower probability of migrating permanently (-0.048), compared with a statistically insignificant increase in the probability of migrating temporarily (0.094). Geographic isolation substantially increases the search costs for permanent offers, reducing this type of migration. In contrast, lucrative, less distantly located temporary opportunities seem to mitigate higher transportation costs.

Assets owned by the 1991 PPS households are found to have no significant effect on either permanent or temporary migration. These estimates suggest that credit and liquidity constraints do not play a substantial role in migration decisions.[24] This finding stands in contrast to the raw means, which indicated that permanent migrants originated from significantly wealthier households, and suggests substantial correlation between initial wealth and other covariates (for instance, age, education, household composition), particularly among permanent migrants.

Temporary migration alone is positively influenced by the 1991 PPS household size. One might expect larger households to facilitate migration by allowing its fixed costs to be spread over more people. However, that is assuming the origin household benefits from the migration decision. Temporary migration may substantially benefit the origin household, given the relatively high likelihood of remittance receipts and the eventual return of the migrant (Stark and Lucas 1988). In contrast, the benefits of permanent migration may accrue predominantly to the migrant; as a result, certis paribus, having more household members is less likely to influence the migration costs faced by the migrant.

Finally, we observe that migrant networks significantly increase the likelihood of both types of migration, but only when networks are sufficiently dense (in the third tercile). This suggests that as expected, networks assist new migrants in locating employment, either by reducing search costs or by improving the distribution of prospective offers. We cannot reject that being in the third tercile of networks has the same impact on both types of migration. However, given the means of the two migration variables, proportionally this effect is far larger for permanent migration, which we would expect to have higher overall search costs.

Interactions with Migrant Networks

Our model suggests important complementarities between networks and individual characteristics. We thus add interactions of network terciles with the education, ability, and road access variables. Conducting separate F tests to examine the joint significance of search costs and their interaction with networks (see Table 5.3), we find evidence of marginally significant complementarities between network size and search costs for permanent migration (though not for temporary). The search costs—captured by the distance to a primary road, a measure of geographic isolation—that previously reduced selection into permanent migration are almost perfectly offset by the presence of dense (third-tercile) networks, indicating that strong migrant networks substantially mitigate search costs. For the bottom tercile of networks, however, search costs significantly reduce permanent migration. Because only very dense networks mitigate the search costs associated with permanent migration, and only for those who are the most geographically most isolated, networks seem to confer (costly) information about job opportunities—particularly for long-distance, permanent moves. In contrast, if networks simply provided referrals, we would not expect their benefits to vary with the search costs implied by an individual's location. Further, our estimates suggest that moderate networks are insufficient to mitigate search costs, nor do networks significantly reduce search costs for those who are less geographically isolated.

[24] A possible explanation for the absence of an effect is that our measure of asset wealth is a poor proxy for the resources used to fund migration. We alternatively included a measure of landholdings as a proxy for assets, which was similarly uncorrelated with the probability of migrating permanently or temporarily. Results available upon request.

Table 5.3 Migrant selection with network interactions

Variable	(1) Permanent	(2) Temporary	(2)-(1) Difference
KPK province (1991)	-0.197	-0.078	0.119
	(0.067)***	(0.084)	[0.281]
Sindh province (1991)	0.012	-0.076	-0.088
	(0.023)	(0.036)**	[0.029]
Age 25–34	0.087	-0.064	-0.151
	(0.040)**	(0.050)	[0.019]
Age 35–44	0.079	-0.088	-0.166
	(0.030)**	(0.053)	[0.005]
Age 45–54	0.084	-0.077	-0.161
	(0.033)**	(0.059)	[0.023]
Age 55–64	0.135	-0.090	-0.225
	(0.064)**	(0.057)	[0.007]
Ever married	-0.012	0.001	0.013
	(0.029)	(0.037)	[0.781]
1991 HH size, tercile two	0.009	0.064	0.055
	(0.033)	(0.050)	[0.162]
1991 HH size, tercile three	0.039	0.120	0.081
	(0.057)	(0.058)**	[0.173]
1991 No. children in HH, tercile two	-0.023	0.007	0.030
	(0.040)	(0.038)	[0.432]
1991 No. children in HH, tercile three	-0.039	-0.071	-0.032
	(0.060)	(0.056)	[0.577]
Complete primary education	-0.014	-0.037	-0.023
	(0.029)	(0.038)	[0.600]
× Migrant networks, tercile two	-0.007	0.047	0.055
	(0.050)	(0.066)	[0.496]
× Migrant networks, tercile three	-0.050	0.022	0.072
	(0.071)	(0.070)	[0.509]
Complete secondary education	0.050	0.171	0.121
	(0.055)	(0.049)***	[0.022]
× Migrant networks, tercile two	-0.109	-0.207	-0.098
	(0.083)	(0.067)***	[0.345]
× Migrant networks, tercile three	-0.093	-0.139	-0.046
	(0.070)	(0.091)	[0.692]
Higher than secondary education	0.132	-0.005	-0.137
	(0.075)*	(0.056)	[0.043]
× Migrant networks, tercile two	-0.182	-0.043	0.139
	(0.106)*	(0.072)	[0.230]
× Migrant networks, tercile three	-0.223	0.031	0.254
	(0.089)**	(0.088)	[0.016]
Digitspan Z score	-0.008	0.027	0.035
	(0.052)	(0.035)	[0.508]
× Migrant networks, tercile two	0.034	0.038	0.004
	(0.074)	(0.045)	[0.958]
× Migrant networks, tercile three	0.147	0.071	-0.077
	(0.060)**	(0.042)*	[0.219]
1991 HH assets, tercile two	0.019	-0.028	-0.047
	(0.034)	(0.031)	[0.223]
1991 HH assets, tercile three	0.029	0.036	0.007
	(0.042)	(0.039)	[0.825]

Table 5.3 Continued

Variable	(1) Permanent	(2) Temporary	(2)-(1) Difference
Dist. to primary road, tercile two	-0.123	-0.043	0.081
	(0.109)	(0.208)	[0.753]
× Migrant networks, tercile two	0.065	0.033	-0.032
	(0.148)	(0.188)	[0.900]
× Migrant networks, tercile three	0.197	0.098	-0.099
	(0.134)	(0.206)	[0.713]
Dist. to primary road, tercile three	-0.270	-0.053	0.218
	(0.106)**	(0.116)	[0.096]
× Migrant networks, tercile two	0.168	0.205	0.037
	(0.165)	(0.133)	[0.791]
× Migrant networks, tercile three	0.272	0.104	-0.168
	(0.122)**	(0.128)	[0.208]
Migrant networks, tercile two	-0.027	-0.032	-0.005
	(0.103)	(0.079)	[0.966]
Migrant networks, tercile three	-0.019	0.010	0.029
	(0.103)	(0.103)	[0.813]
Constant	0.214	0.272	
	(0.094)**	(0.111)**	
R^2	0.09	0.08	
N	1,103	1,198	
F test p-val: Digitspan-network variables = 0	0.01	0.23	
F test p-val: Education-network variables = 0	0.14	0.08	
F test p-val: Road-network variables = 0	0.09	0.48	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: HH = household. KPK = Khyber Pakhtunkhwa. Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$; *** $p < 0.01$. P-values in brackets for statistical difference in coefficient estimates across models.

Complementarities between networks and skill are strong and offer perhaps the most interesting motivation for empirically distinguishing between temporary and permanent migration. As shown in Table 5.3, high-ability individuals are more likely to engage in permanent migration only when they have access to dense (in the third tercile) migrant networks. Again, this effect is much larger in magnitude for permanent migration, which tends to entail greater returns on ability. Conditional on having a network size within the third tercile, a 1 standard deviation increase in the Digit Span score increases the likelihood of permanent migration by 14.7 percentage points, compared with the sample mean of 18.1 percent. But in the absence of strong networks, ability has no significant effect on either type of migration. Nor do networks confer benefits irrespective of ability; the direct effect of networks on those with low ability is much smaller in magnitude and not statistically significant. These nuanced impacts may reflect strategic behavior on the part of the network, such as an effort to safeguard network quality by providing costly job information and referrals only to high-ability workers. Alternatively, strong networks may provide information, but only high-ability people can benefit from it.

Interactions between education and networks are more complex. In our basic specification (Table 5.2), education did not significantly affect either type of migration. But when we add interactions with networks, we find statistically significant evidence of positive selection among permanent migrants and intermediate selection among temporary migrants—though only in the case of weak migrant networks. In contrast, for moderate or dense networks, we find significant negative complementarities between networks and formal education that exceed the direct effects of education for both temporary and permanent migration. Those with more than secondary education are 13.2 percentage points more likely to engage in permanent migration, all else equal. But if they also have access to moderate (second-tercile) or dense (third-tercile) networks, they are 5.0 and 8.1 percentage points, respectively, less likely to migrate permanently than an individual with less than primary education and weak networks. In the case of temporary migration, individuals with secondary education are 17.1 percentage points more likely to migrate when they have weak networks. But if they also have access to moderate (second-tercile) networks, they are 3.6 percentage points less likely to migrate.

What emerges from these results is a nuanced role for networks in the job search process. Without strong networks, ability has no significant effect on migration, while the opposite is true for education. These opposite findings are intuitive; while ability may be the main determinant of worker productivity, education is much more readily observable to employers. Therefore, our results suggest that, when entering a new labor market, those with weak networks must rely more heavily on credentials than on underlying ability. Put differently, potential migrants cannot rely on innate ability without either networks as a complement or credentials as a signal. Conversely, moderate and dense networks assist in migration for high-ability workers yet appear to deter the migration of highly educated workers.

The results offer interesting insights about the dynamics of migrant labor markets and networks in Pakistan. First, it is possible that the returns to tertiary (secondary) education are actually low for permanent (temporary) migrants. Individuals with weak networks may have less accurate priors about these returns, resulting in more migration than is optimal. Second, networks may be less willing to assist the highly educated in pursuit of migrant employment. This could occur if there are local concerns about "brain drain" or if there is internal competition within a thin labor market (Calvo-Armengol 2004) such that additional migration of educated workers will significantly reduce expected wages. While a complete analysis of the returns to education is beyond the scope of this paper, the latter is consistent with cursory evidence from data in several Pakistani Labor Force Surveys. In Table 5.4, we report regressions of wages and unemployment on age and education for males aged 22–60. Tertiary education provides no wage gains above and beyond those of secondary education and carries a significantly higher probability of unemployment. Although studies describing the labor markets in Pakistan are limited, recent case studies suggest a trend of increased tertiary education in conjunction with overqualification in occupational choices (Farooq, Ahmed, and Ali 2008; World Bank 2013). This situation leads to low returns and high unemployment. Below, we explore how network quality influences these relationships.

Table 5.4 Mincerian wage regressions

Variable	Ln(Wage)	Unemployment
Age 25–34	0.138***	-0.026***
	(0.012)	(0.003)
Age 35–44	0.298***	-0.047***
	(0.015)	(0.005)
Age 45–54	0.392***	-0.034***
	(0.016)	(0.005)
Age 55–64	0.358***	-0.017***
	(0.022)	(0.006)
Completed primary education	0.308***	0.007***
	(0.014)	(0.002)
Completed secondary education	0.865***	0.042
	(0.065)	(0.028)
Completed higher than secondary education	0.835***	0.024***
	(0.026)	(0.006)
Constant	8.511***	0.069***
	(0.022)	(0.003)
R-squared	0.289	0.016
N	36,351	90,561

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: District-clustered standard errors in parentheses. * p < 0.1 ** p < 0.05; *** p < 0.01. District and year fixed effects included.

Robustness

Attrition

We first provide regression estimates including untracked migrants to demonstrate the sensitivity of our estimates to their exclusion. For untracked individuals, we lack two explanatory variables: education[25] and the Digit Span score. However, we have data from their origin households on other variables. Our estimates are reasonably stable when attritors are added to the sample (Table A.3).[26] These findings suggest that the results may not be driven by sample attrition, with one exception pertaining to the age profile of permanent migrants. Once attritors are included, we observe no significant differences in permanent migration across age groups, although our main sample displays a significant positive relationship with age.

We next examine how our results may be affected by selective attrition using the inverse probability weights recommended by Fitzgerald, Gottschalk, and Moffitt (1998).[27] The weighted regression version of Table 5.3 is shown in Table A.5. Inferences are similar when accounting for attrition, with the exception that the negative effect of being 35 to 44 years old gains significance in the temporary migration regression. The weighted specification appears to improve the overall precision of the coefficient estimates with negligible consequence on interpretation.

Alternative Measures of Cognitive Ability

We replicate the basic permanent and temporary migration regressions (omitting interaction variables) with alternative measures of cognitive ability: forward Digit Span, backward Digit Span, total Raven score (sections A, B, and D), Raven A, Raven B, Raven D, and height z-score. The ability parameter and standard error estimates from each specification are reported in Table 5.5. In none of the models can we reject that the estimated parameters on the ability measures are statistically different across permanent and temporary migration—consistent with our findings in Table 5.2 using the overall Digit Span. Variation in the more challenging component of the Digit Span test—backward memorization—appears to be driving the ability estimates. Scores from section A of the Raven test corroborate a positive effect on both forms of migration, although it is only statistically significant in the temporary migration equation. Height—a visual measure of ability—does not predict either form of migration, controlling for education. This result suggests that nutrition and educational outcomes are likely jointly determined by the household (Vogl 2014). It also suggests that migrant labor markets do not reward "brawn" over "brains" (Pitt, Rosenzweig, and Hassan 2012).

[25] We are missing education levels for a fraction of the untracked migrants because many were young when last surveyed in 1991. For those with some education in 1991, we are unable to infer what their completed education levels were in 2013–2014.

[26] The 180 untracked individuals in Figure 3.1 can be stratified into 124 permanent migrants, 29 temporary migrants, and 27 nonmigrants based on additional information on the tracking rosters. We add 124 permanent migrants and 27 nonmigrants to the original permanent migrant sample (originally 1,103 observations). We add 29 migrants and 27 nonmigrants to the temporary migrant sample (originally 1,198 observations).

[27] We estimate restricted and unrestricted (with supervisor indicators and village attrition rate as instruments) probit regressions to formulate inverse probability weights. Table A.4 shows the unrestricted results.

Table 5.5 Migrant selection with alternative measures of cognitive ability

Variable	Permanent migration coeff. (SE)	R-squared	Temporary migration coeff. (SE)	R-squared	Difference [p-val]
Digit Span (overall)	0.067	0.06	0.067	0.06	-0.000
	(0.037)*		(0.019)***		[0.997]
Digit Span (forward)	0.031	0.06	0.056	0.06	0.025
	(0.031)		(0.019)***		[0.420]
Digit Span (backward)	0.071	0.07	0.049	0.06	-0.022
	(0.030)**		(0.018)***		[0.556]
Raven (overall)	0.002	0.05	0.006	0.06	0.004
	(0.019)		(0.013)		[0.869]
Raven (A)	0.013	0.05	0.021	0.06	0.007
	(0.015)		(0.010)**		[0.685]
Raven (B)	-0.003	0.05	-0.001	0.06	0.003
	(0.015)		(0.015)		[0.884]
Raven (D)	-0.004	0.05	-0.006	0.06	-0.002
	(0.020)		(0.016)		[0.934]
Height	0.008	0.05	0.021	0.06	0.014
	(0.013)		(0.016)		[0.453]

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$; *** $p < 0.01$. P-values in brackets for statistical difference in coefficient estimates across models. The number of observations in the permanent and temporary migration regressions are 1,103 and 1,198, respectively. Specifications follow those estimated in Table 5.3, replacing the Digit Span (overall) score with the ability measures listed above. For brevity, only the coefficient and standard error estimates of the ability coefficients are reported.

We next use the alternative measures of ability in the interacted model. Table A.6 measures ability with the three Digit Span scores and height, while Table A.7 measures ability with Raven scores. In each table, we display the estimated parameters and standard errors for the ability, education, and network variables. Overall, these estimates are consistent with our main findings above. The direct effect of cognitive ability is not statistically significant for any measure. The positive and significant interaction between ability and networks is quite robust to the measures derived from the Digit Span test, but not when using components from the Raven test or height. The direct effects of education are also found to be positive and significant, as are the negative and significant interactions between education and networks. Both sets of effects are robust to all specifications of cognitive ability. However, the coefficients related to more than secondary education are significant only when overall or forward Digit Span is used, implying stronger correlation between high levels of education and more challenging cognitive tests (backward Digit Span, Raven).

These findings, though consistent with Kaestner and Malamud (2014), may be specific to prevailing labor market conditions. That is, the Digit Span test is largely considered a “simple” task that measures short-term recall and working memory, while Raven’s Progressive Matrices measure fluid intelligence involving inductive reasoning (Fry and Hale 1996). The Digit Span, therefore, may be more relevant for work requiring the learning and repetition of simple to moderately difficult tasks without higher-order cognitive processing, while the Raven test would be more relevant for highly skilled positions involving a great deal of inductive reasoning. Moreover, formal education may have a larger effect on test scores for fluid intelligence than those for memory (Jaeggi et al. 2008), suggesting that the effect of Raven scores will be minimal when controls for education are also included. In light of these differences, future surveys should consider carefully the choice of cognitive tests.

Exploring Network Definitions

Our last set of specifications explores the implications of using narrower definitions of the migrant network: focusing only on network members who (1) have an above-median Digit Span score, (2) have completed secondary education or higher, and (3) are above the sample median age. The results for permanent migration (Table A.8) are very similar in sign and significance to our main results (Table 5.3), suggesting that network-skill interactions are not driven by the quality of the network. Network quality does magnify the effects, with point estimates considerably larger. However, the direct effect of education is no longer statistically significant and is much smaller in magnitude. This may point to a correlation between network quality and formal education.

The findings for temporary migration are sensitive to the choice of network definition. A positive interaction between ability and networks is now evident only for high-ability networks, and the point estimates are twice as large as in Table 5.3. High-ability networks appear to strongly support temporary migration for high-ability workers, but high-education networks do not do the same, nor do they deter migration among the highly educated. Taken together, these results suggest that with regard to temporary migration, it is the low-ability, low-education network members that deter migration among the highly educated.[28]

Finally, as a proxy for the tenure of the network contacts, we exclude from the network community members who are below the sample median age.[29] These contacts have more experience in the destination location to improve a potential migrant's employment prospects, and are arguably less vulnerable to pressures of competition. We find that older contacts continue to drive the permanent migration of highly able workers. Yet the negative selection previously observed among highly educated workers with larger networks is smaller in magnitude (though imprecisely estimated). These findings confirm that the network-education dynamics are likely driven by the inelastic demand for skilled labor in permanent migrant labor markets. However, tenured networks can soften the selection effects associated with highly educated workers.

[28] One possible explanation for this result is that low-skilled networks may understate the returns to education in temporary employment opportunities. Educated workers will formulate beliefs based on this information, and given their pessimistic income expectations they may be less likely to migrate. Given a similar skill profile, those with weak networks will have noisy but unbiased beliefs about the returns to education.

[29] Migrant age is used as a proxy for migrant tenure (years away from the origin household) because we lack data on the year and duration of temporary migration episodes, as in Munshi (2003) and Beaman (2012).

6. CONCLUSION

Existing literature on migration largely fails to separately model two distinct types of migrants: temporary and permanent. We address this by utilizing a search model to illustrate the two migration decisions and then using a unique panel dataset with detailed migration information from rural Pakistan spanning 1991–2013 to test the model. Patterns of selection are found to vary with the duration of the migration episode, consistent with differences in search costs and the scope for employer-employee matching and returns to experience.

We find clear evidence of positive selection on skill among permanent migrants, suggesting that skill is a key factor in obtaining good permanent wage offers. Networks appear to facilitate job matching in the permanent migrant labor market for those with strong cognitive skills, perhaps to improve network quality or perhaps because other labor markets are relatively easy to enter without network assistance. Conversely, temporary migrants display much weaker selection on skills, consistent with the idea that since temporary migration opportunities are located through a spot market, it is difficult to signal skill, resulting in relatively low returns. The links between migration, education, and networks, however, are found to be much more nuanced and highly dependent on prevailing labor market conditions. We also find that search costs—proxied by distance to a primary road—significantly reduce permanent migration, though only in the absence of strong networks. Strong networks nearly perfectly offset the negative impacts of search costs on permanent migration. Overall, these findings underscore the importance of studying temporary and permanent migration separately. The duration of the migration episode has important implications for the type of individual that chooses to migrate, meriting greater attention in the literature.

APPENDIX: SUPPLEMENTARY TABLES

Table A.1 Attritor characteristics

Variable	Tracked migrant mean	Untracked individuals mean	Difference (p-value)	Untracked households mean	Difference (p-value)
Age	37.10	35.92	0.19	33.91	0.00
1991 head's years of schooling 1991	3.49	4.31	0.04	1.25	0.00
number of children	5.48	5.23	0.49	6.86	0.00
1991 household sze	12.70	12.12	0.29	13.03	0.56
1991 durable assets (1,000 rupees)	111.71	151.60	0.05	25.57	0.00
1991 total owned land (acres)	8.58	10.02	0.43	5.30	0.05
KPK province	0.28	0.32	0.39	0.21	0.08
Sindh province	0.16	0.19	0.33	0.69	0.00
N	391	180		154	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).
Note: KPK = Khyber Pakhtunkhwa.

Table A.2 Migrant selection with network interactions (logit)

Variable	(1) Permanent	(2) Temporary	(2)-(1) Difference
Province of 1991 village is KPK	-0.133**	-0.047	0.107
	(0.057)	(0.080)	[0.254]
Province of 1991 village is Sindh	0.034	-0.082**	-0.118
	(0.029)	(0.040)	[0.011]
Age 25-34	0.118**	-0.054	-0.186
	(0.050)	(0.042)	[0.009]
Age 35-44	0.109***	-0.078*	-0.198
	(0.038)	(0.047)	[0.001]
Age 45-54	0.112***	-0.071	-0.192
	(0.042)	(0.055)	[0.007]
Age 55-64	0.162***	-0.083	-0.259
	(0.057)	(0.054)	[0.001]
Married (presently or in past)	-0.011	0.000	0.014
	(0.028)	(0.035)	[0.759]
1991 number of HH members, second tercile	0.003	0.062	0.052
	(0.030)	(0.048)	[0.135]
1991 number of HH members, third tercile	0.043	0.115**	0.046
	(0.053)	(0.055)	[0.438]
1991 number of child HH members, second tercile	-0.016	0.009	0.030
	(0.043)	(0.039)	[0.503]
1991 number of child HH members, third tercile	-0.039	-0.066	-0.003
	(0.059)	(0.056)	[0.965]
Community networks, second tercile	0.014	0.010	-0.028
	(0.105)	(0.074)	[0.835]
Community networks, third tercile	0.059	0.060	-0.042
	(0.105)	(0.095)	[0.748]

Table A.2 Continued

Variable	(1) Permanent	(2) Temporary	(2)-(1) Difference
Complete primary education	-0.061	-0.060	0.032
	(0.089)	(0.067)	[0.780]
× Community networks, second tercile	0.041	0.064	0.004
	(0.098)	(0.090)	[0.974]
× Community networks, third tercile	0.027	0.058	0.000
	(0.099)	(0.085)	[0.998]
Completed secondary education	0.034	0.143***	0.096
	(0.089)	(0.033)	[0.350]
× Community networks, second tercile	-0.107	-0.181***	-0.031
	(0.113)	(0.061)	[0.840]
× Community networks, third tercile	-0.046	-0.099	-0.061
	(0.096)	(0.070)	[0.629]
Completed higher than secondary education	0.084	-0.022	-0.099
	(0.092)	(0.069)	[0.348]
× Community networks, second tercile	-0.142	-0.034	0.147
	(0.099)	(0.085)	[0.208]
× Community networks, third tercile	-0.118	0.062	0.151
	(0.103)	(0.091)	[0.238]
Digit Span Z score	0.063**	0.062***	-0.049
	(0.029)	(0.017)	[0.326]
× Community networks, second tercile	-0.037*	0.008	0.034
	(0.019)	(0.021)	[0.427]
× Community networks, second tercile	0.000	-0.016	0.039
	(0.026)	(0.031)	[0.293]
1991 assets, second tercile	0.026	-0.031	-0.052
	(0.037)	(0.035)	[0.250]
1991 assets, third tercile	0.041	0.030	-0.018
	(0.041)	(0.038)	[0.586]
Distance from primary road, second tercile	0.022	0.020	-0.058
	(0.064)	(0.163)	[0.730]
× Community networks, second tercile	0.013	-0.003	0.009
	(0.074)	(0.137)	[0.956]
× Community networks, third tercile	0.019	0.014	0.053
	(0.082)	(0.161)	[0.763]
Distance from primary road, third tercile	-0.148**	0.021	0.156
	(0.067)	(0.092)	[0.093]
× Community networks, second tercile	0.128	0.155	-0.011
	(0.103)	(0.112)	[0.920]
× Community networks, third tercile	0.138	0.005	-0.100
	(0.086)	(0.105)	[0.312]
N	1,103	1,198	
F test p-val: Digit Span-network variables = 0	0.12	0.82	
F test p-val: Education-network variables = 0	0.56	0.01	
F test p-val: Wage-network variables = 0	0.15	0.54	
F test p-val: Road-network variables = 0	1,103	1,198	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: KPK = Khyber Pakhtunkhwa; HH = household. P-values in brackets for statistical difference in coefficient estimates across models. Logit model reports marginal effects.

Table A.3 Migrant selection, including attritors

Variable	Permanent migration Old	New	Temporary migration Old	New
KPK province (1991)	-0.043	-0.025	0.049	0.037
	(0.042)	(0.060)	(0.083)	(0.082)
Sindh province (1991)	0.009	-0.066	-0.095	-0.122
	(0.032)	(0.052)	(0.040)**	(0.042)***
Age 25–34	0.081	0.008	-0.079	-0.086
	(0.037)**	(0.052)	(0.046)*	(0.049)*
Age 35–44	0.074	0.022	-0.103	-0.118
	(0.024)***	(0.045)	(0.051)*	(0.053)**
Age 45–54	0.064	-0.024	-0.105	-0.130
	(0.030)**	(0.034)	(0.051)**	(0.051)**
Age 55–64	0.111	-0.028	-0.127	-0.155
	(0.056)*	(0.077)	(0.052)**	(0.057)***
1991 HH size, tercile two	0.018	0.023	0.069	0.056
	(0.037)	(0.042)	(0.049)	(0.049)
1991 HH size, tercile three	0.027	-0.013	0.122	0.092
	(0.060)	(0.076)	(0.060)**	(0.063)
1991 number of children in HH, tercile two	-0.014	0.012	0.013	0.018
	(0.045)	(0.053)	(0.043)	(0.043)
1991 number of children in HH, tercile three	-0.024	0.057	-0.063	-0.042
	(0.068)	(0.099)	(0.059)	(0.062)
1991 HH assets, tercile two	0.028	0.004	-0.024	-0.027
	(0.034)	(0.042)	(0.032)	(0.033)
1991 HH assets, tercile three	0.051	0.084	0.055	0.062
	(0.045)	(0.061)	(0.041)	(0.042)
Dist. to primary road, tercile two	0.052	0.091	0.028	0.016
	(0.050)	(0.085)	(0.078)	(0.080)
Dist. to primary road, tercile three	-0.057	0.040	0.089	0.080
	(0.042)	(0.062)	(0.074)	(0.070)
Migrant networks, tercile two	0.005	0.029	0.027	0.029
	(0.039)	(0.052)	(0.050)	(0.048)
Migrant networks, tercile three	0.081	0.145	0.103	0.093
	(0.043)*	(0.053)***	(0.045)**	(0.049)*
Constant	0.028	0.096	0.167	0.217
	(0.056)	(0.076)	(0.087)*	(0.099)**
R^2	0.05	0.06	0.05	0.05
N	1,103	1,253	1,198	1,254

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: PK = Khyber Pakhtunkhwa; HH = household. Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$; *** $p < 0.01$. One permanent migrant attritor observation was dropped due to a missing value for at least one of the explanatory variables.

Table A.4 Probability of remaining in sample

Variable	Dummy – in sample
Born in 1962 to 1976	-0.06**
	(0.03)
Born in 1977 to 1991	-0.08***
	(0.03)
1991 assets, second tercile	0.02
	(0.03)
1991 assets, third tercile	-0.09**
	(0.04)
1991 number of HH members, second tercile	0.00
	(0.02)
1991 number of members, third tercile	0.03
	(0.03)
Percent of 1991 village members that attrited	-0.34***
	(0.08)
Supervisor indicator 2	-0.04
	(0.03)
Supervisor indicator 3	-0.78***
	(0.09)
Supervisor indicator 4	-0.82***
	(0.08)
Province of 1991 village is KPK	0.78***
	(0.09)
Province of 1991 village is Sindh	0.75***
	(0.08)
N	1,525

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: KPK = Khyber Pakhtunkhwa; HH = household. Marginal effects presented. Standard errors in parentheses. *p < 0.1 ** p < 0.05; *** p < 0.01. There were 18 supervisors, but only four supervisors had attritors under their supervision. One observation was omitted because it was missing at least one explanatory variable.

Table A.5 Migrant selection with network interactions, inverse probability weights

Variable	(1) Permanent	(2) Temporary	(2)-(1) Difference
Province of 1991 village is KPK	-0.207	-0.089	0.117
	(0.064)***	(0.082)	[0.277]
Province of 1991 village is Sindh	0.007	-0.074	-0.080
	(0.024)	(0.036)**	[0.052]
Age 25–34	0.083	-0.067	-0.151
	(0.038)**	(0.049)	[0.016]
Age 35–44	0.072	-0.091	-0.163
	(0.029)**	(0.053)*	[0.005]
Age 45–54	0.083	-0.079	-0.162
	(0.032)**	(0.059)	[0.021]
Age 55–64	0.129	-0.093	-0.223
	(0.062)**	(0.057)	[0.006]
Married (presently or in past)	-0.009	-0.000	0.009
	(0.028)	(0.036)	[0.855]
1991 no. of HH members, second tercile	0.008	0.059	0.051
	(0.032)	(0.049)	[0.199]
1991 no. of HH members, third tercile	0.037	0.118	0.081
	(0.055)	(0.059)	[0.163]
1991 no. of child HH members, second tercile	-0.019	0.010	0.029
	(0.040)	(0.039)	[0.462]
1991 no. of child HH members, third tercile	-0.038	-0.066	-0.027
	(0.059)	(0.056)	[0.634]
Community networks, second tercile	-0.033	-0.050	-0.017
	(0.098)	(0.083)	[0.868]
Community networks, third tercile	-0.025	-0.009	0.017
	(0.096)	(0.105)	[0.886]
Completed primary education	-0.012	-0.039	-0.028
	(0.028)	(0.038)	[0.527]
x Community networks, second tercile	-0.009	0.051	0.059
	(0.049)	(0.066)	[0.447]
x Community networks, third tercile	-0.047	0.028	0.075
	(0.069)	(0.070)	[0.484]
Completed secondary education	0.045	0.171	0.126
	(0.052)	(0.049)***	[0.013]
× Community networks, second tercile	-0.116	-0.209	-0.093
	(0.077)	(0.066)***	[0.345]
× Community networks, third tercile	-0.084	-0.133	-0.048
	(0.066)	(0.090)	[0.671]
Completed higher than secondary education	0.129	-0.003	-0.132
	(0.072)*	(0.057)	[0.044]
× Community networks, second tercile	-0.185	-0.050	0.135
	(0.102)*	(0.073)	[0.222]
× Community networks, third tercile	-0.214	0.040	0.254
	(0.087)**	(0.093)	[0.016]
Digit Span z-score	-0.009	0.021	0.029
	(0.051)	(0.037)	[0.560]
× Community networks, second tercile	0.043	0.049	0.006
	(0.071)	(0.048)	[0.935]
× Community networks, second tercile	0.144	0.075	-0.069
	(0.058)**	(0.044)*	[0.261]
1991 assets, second tercile	0.021	-0.028	-0.049
	(0.033)	(0.031)	[0.198]
1991 assets, third tercile	0.026	0.036	0.011
	(0.041)	(0.040)	[0.722]

Table A.5 Continued

Variable	(1) Permanent	(2) Temporary	(2)-(1) Difference
Distance from primary road, second tercile	0.007	0.027	-0.071
	(0.070)	(0.195)	[0.755]
× Community networks, second tercile	0.016	-0.013	0.040
	(0.086)	(0.173)	[0.856]
× Community networks, third tercile	0.067	0.004	0.054
	(0.110)	(0.200)	[0.825]
Distance from primary road, third tercile	-0.131	0.000	0.047
	(0.067)*	(0.098)	[0.618]
× Community networks, second tercile	0.078	0.164	0.139
	(0.096)	(0.120)	[0.181]
× Community networks, third tercile	0.129	0.031	0.020
	(0.097)	(0.127)	[0.849]
Constant	0.127	0.247	
	(0.076)	(0.109)**	
R^2	0.08	0.08	
N	1,103	1,198	
F test p-val: Digit Span-network variables = 0	0.11	0.84	
F test p-val: Education-network variables = 0	0.67	0.07	
F test p-val: Road-network variables = 0	0.61	0.70	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: KPK = Khyber Pakhtunkhwa; HH = household. Standard errors in parentheses. * p < 0.1 ** p < 0.05; *** p < 0.01. P-values in brackets for statistical difference in coefficient estimates across models.

Table A.6 Migrant selection with network interactions and alternative measures of cognitive ability: Digit Span

Ability measure	Digit Span (overall)			Digit Span (forward)			Digit Span (backward)			Height		
Migration equation	Perm.	Temp.	Diff. [p-val]	Perm.	Temp.	Diff. [p-val]	Perm.	Temp.	Diff.	Perm.	Temp.	Diff. [p-val]
Complete primary education	-0.014	-0.037	-0.023	0.000	-0.051	-0.052	-0.021	-0.023	-0.002	-0.008	-0.035	-0.027
	(0.029)	(0.038)	[0.600]	(0.026)	(0.039)	[0.257]	(0.031)	(0.038)	[0.961]	(0.026)	(0.037)	[0.518]
× Migrant networks, tercile two	-0.007	0.047	0.055	-0.012	0.067	0.079	-0.001	0.038	0.039	-0.008	0.063	0.071
	(0.050)	(0.066)	[0.496]	(0.049)	(0.068)	[0.341]	(0.050)	(0.067)	[0.645]	(0.049)	(0.071)	[0.432]
× Migrant networks, tercile three	-0.050	0.022	0.072	-0.064	0.033	0.097	-0.026	0.025	0.051	-0.018	0.055	0.074
	(0.071)	(0.070)	[0.509]	(0.067)	(0.073)	[0.366]	(0.073)	(0.068)	[0.637]	(0.071)	(0.067)	[0.487]
Completed secondary education	0.050	0.171	0.121	0.069	0.149	0.079	0.033	0.196	0.163	0.047	0.180	0.132
	(0.055)	(0.049)***	[0.022]	(0.055)	(0.048)***	[0.123]	(0.054)	(0.048)***	[0.002]	(0.056)	(0.050)***	[0.024]
× Migrant networks, tercile two	-0.109	-0.207	-0.098	-0.107	-0.171	-0.065	-0.096	-0.222	-0.126	-0.091	-0.173	-0.082
	(0.083)	(0.067)***	[0.345]	(0.081)	(0.068)**	[0.534]	(0.077)	(0.066)***	[0.214]	(0.070)	(0.072)**	[0.436]
× Migrant networks, tercile three	-0.093	-0.139	-0.046	-0.101	-0.119	-0.018	-0.055	-0.145	-0.090	-0.026	-0.103	-0.077
	(0.070)	(0.091)	[0.692]	(0.068)	(0.098)	[0.869]	(0.073)	(0.087)	[0.452]	(0.071)	(0.090)	[0.492]
Completed higher than secondary education	0.132	-0.005	-0.137	0.165	-0.036	-0.201	0.108	0.029	-0.079	0.128	0.008	-0.120
	(0.075)*	(0.056)	[0.043]	(0.064)**	(0.054)	[0.001]	(0.079)	(0.058)	[0.290]	(0.069)*	(0.059)	[0.059]
× Migrant networks, tercile two	-0.182	-0.043	0.139	-0.187	0.011	0.198	-0.165	-0.070	0.095	-0.157	-0.001	0.156
	(0.106)*	(0.072)	[0.230]	(0.093)*	(0.070)	[0.055]	(0.103)	(0.075)	[0.405]	(0.079)*	(0.075)	[0.060]
× Migrant networks, tercile three	-0.223	0.031	0.254	-0.241	0.059	0.300	-0.165	0.030	0.194	-0.115	0.091	0.207
	(0.089)**	(0.088)	[0.016]	(0.079)***	(0.096)	[0.003]	(0.101)	(0.087)	[0.084]	(0.096)	(0.090)	[0.051]
Ability	-0.008	0.027	0.035	-0.042	0.056	0.099	0.022	-0.015	-0.037	-0.019	0.023	0.041
	(0.052)	(0.035)	[0.508]	(0.042)	(0.036)	[0.025]	(0.046)	(0.028)	[0.438]	(0.021)	(0.018)	[0.152]
× Migrant networks, tercile two	0.034	0.038	0.004	0.039	-0.018	-0.057	0.017	0.079	0.062	0.031	-0.000	-0.031
	(0.074)	(0.045)	[0.958]	(0.059)	(0.043)	[0.334]	(0.064)	(0.040)*	[0.413]	(0.028)	(0.030)	[0.396]
× Migrant networks, tercile three	0.147	0.071	-0.077	0.151	0.028	-0.123	0.096	0.091	-0.005	0.045	-0.005	-0.050
	(0.060)**	(0.042)*	[0.219]	(0.050)***	(0.043)	[0.014]	(0.055)*	(0.037)**	[0.937]	(0.032)	(0.025)	[0.157]
Migrant networks, tercile two	-0.014	-0.037	-0.005	-0.036	-0.002	0.034	-0.019	-0.061	-0.042	-0.022	-0.025	-0.004
	(0.029)	(0.038)	[0.966]	(0.096)	(0.081)	[0.753]	(0.098)	(0.071)	[0.701]	(0.082)	(0.064)	[0.967]
Migrant networks, tercile three	0.050	0.171	0.029	-0.009	0.045	0.054	-0.005	-0.010	-0.005	0.018	0.043	0.025
	(0.055)	(0.049)***	[0.813]	(0.100)	(0.106)	[0.666]	(0.104)	(0.098)	[0.963]	(0.105)	(0.101)	[0.832]
R^2	0.09	0.08		0.08	0.08		0.09	0.08		0.07	0.07	
F test p-val:												
Ability-network variables = 0	0.01	0.23		0.00	0.33		0.12	0.04		0.36	0.98	
Education-network variables = 0	0.14	0.08		0.04	0.15		0.40	0.04		0.47	0.09	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: KPK = Khyber Pakhtunkhwa; HH = household. Marginal effects presented. Standard errors in parentheses. * $p < 0.1$ ** $p < 0.05$; *** $p < 0.01$. P-values in brackets for statistical difference in coefficient estimates across models. The number of observations in the permanent and temporary migration regressions are 1,103 and 1,198, respectively. Specifications follow those estimated in Table 5.4, replacing the Digit Span (overall) score with the ability measures listed above. For brevity, only the coefficient and standard error estimates of the ability coefficients are reported.

Table A.7 Migrant selection with network interactions and alternative measures of cognitive ability: Raven

Ability measure	Raven (overall)			Raven (A)			Raven (B)			Raven (D)		
Migration equation	Perm.	Temp.	Diff. [p-val]	Perm.	Temp.	Diff. [p-val]	Perm.	Temp.	Diff. [p-val]	Perm.	Temp.	Diff. [p-val]
Completed primary education	-0.020	-0.029	-0.009	-0.015	-0.033	-0.018	-0.020	-0.032	-0.013	-0.016	-0.025	-0.009
	(0.031)	(0.036)	[0.826]	(0.029)	(0.038)	[0.683]	(0.032)	(0.036)	[0.766]	(0.030)	(0.037)	[0.835]
× Migrant networks, tercile two	0.010	0.056	0.046	0.002	0.060	0.058	0.013	0.065	0.052	0.003	0.053	0.051
	(0.051)	(0.072)	[0.619]	(0.051)	(0.072)	[0.531]	(0.052)	(0.069)	[0.557]	(0.050)	(0.073)	[0.590]
× Migrant networks, tercile three	-0.009	0.053	0.063	-0.022	0.057	0.079	-0.009	0.053	0.061	-0.011	0.046	0.057
	(0.073)	(0.068)	[0.559]	(0.074)	(0.067)	[0.458]	(0.074)	(0.068)	[0.570]	(0.073)	(0.067)	[0.593]
Completed secondary education	0.033	0.184	0.151	0.042	0.177	0.135	0.034	0.179	0.145	0.037	0.195	0.158
	(0.062)	(0.044)***	[0.005]	(0.059)	(0.047)***	[0.010]	(0.060)	(0.042)***	[0.011]	(0.058)	(0.047)***	[0.002]
× Migrant networks, tercile two	-0.067	-0.183	-0.116	-0.081	-0.179	-0.099	-0.062	-0.163	-0.101	-0.075	-0.191	-0.116
	(0.079)	(0.068)***	[0.282]	(0.077)	(0.069)**	[0.354]	(0.078)	(0.062)**	[0.344]	(0.074)	(0.071)**	[0.271]
× Migrant networks, tercile three	-0.015	-0.092	-0.077	-0.040	-0.093	-0.053	-0.010	-0.102	-0.092	-0.004	-0.093	-0.089
	(0.082)	(0.091)	[0.529]	(0.076)	(0.089)	[0.630]	(0.078)	(0.089)	[0.435]	(0.077)	(0.092)	[0.472]
Comleted higher than secondary education	0.105	0.011	-0.094	0.123	0.003	-0.120	0.108	0.003	-0.105	0.110	0.031	-0.078
	(0.070)	(0.058)	[0.171]	(0.066)*	(0.060)	[0.063]	(0.073)	(0.061)	[0.126]	(0.069)	(0.058)	[0.214]
× Migrant networks, tercile two	-0.120	-0.020	0.100	-0.149	-0.012	0.137	-0.117	0.014	0.130	-0.130	-0.044	0.086
	(0.081)	(0.069)	[0.240]	(0.078)*	(0.072)	[0.093]	(0.085)	(0.073)	[0.134]	(0.080)	(0.070)	[0.281]
× Migrant networks, tercile three	-0.101	0.104	0.205	-0.139	0.105	0.243	-0.098	0.095	0.194	-0.090	0.086	0.175
	(0.099)	(0.087)	[0.077]	(0.091)	(0.089)	[0.027]	(0.098)	(0.092)	[0.079]	(0.099)	(0.089)	[0.123]
Ability	0.023	0.005	-0.018	0.005	0.016	0.011	0.028	0.014	-0.014	0.020	-0.025	-0.045
	(0.030)	(0.022)	[0.657]	(0.020)	(0.014)	[0.647]	(0.025)	(0.028)	[0.754]	(0.030)	(0.024)	[0.215]
× Migrant networks, tercile two	-0.039	0.026	0.065	-0.003	0.032	0.035	-0.052	-0.025	0.028	-0.032	0.065	0.098
	(0.029)	(0.027)	[0.178]	(0.024)	(0.024)	[0.255]	(0.026)**	(0.033)	[0.569]	(0.030)	(0.032)**	[0.031]
× Migrant networks, tercile three	-0.011	-0.022	-0.011	0.032	-0.024	-0.056	-0.022	-0.015	0.007	-0.031	-0.008	0.024
	(0.054)	(0.033)	[0.862]	(0.041)	(0.031)	[0.243]	(0.039)	(0.040)	[0.904]	(0.058)	(0.038)	[0.723]
Migrant networks, tercile two	-0.024	-0.023	0.000	-0.019	-0.028	-0.009	-0.030	-0.026	0.004	-0.017	-0.026	-0.009
	(0.082)	(0.062)	[0.998]	(0.082)	(0.062)	[0.924]	(0.082)	(0.062)	[0.968]	(0.082)	(0.063)	[0.922]
Migrant networks, tercile three	0.032	0.048	0.016	0.036	0.044	0.007	0.031	0.049	0.018	0.033	0.051	0.018
	(0.101)	(0.098)	[0.891]	(0.103)	(0.099)	[0.949]	(0.100)	(0.097)	[0.874]	(0.102)	(0.098)	[0.874]
R^2	0.07	0.07		0.07	0.07		0.07	0.07		0.07	0.07	
F test p-val:												
Ability-network variables = 0	0.33	0.39		0.65	0.20		0.11	0.76		0.56	0.08	
Education-network variables = 0	0.76	0.05		0.53	0.06		0.77	0.09		0.71	0.05	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: KPK = Khyber Pakhtunkhwa; HH = household. Marginal effects presented. Standard errors in parentheses. *p< 0.1 ** p< 0.05; *** p< 0.01. P-values in brackets for statistical difference in coefficient estimates across models. The number of observations in the permanent and temporary migration regressions are 1,103 and 1,198, respectively. Specifications follow those estimated in Table 5.4, replacing the Digit Span (overall) score with the ability measures listed above. For brevity, only the coefficient and standard error estimates of the ability coefficients are reported.

Table A.8 Migrant selection with network interactions and alternative network definitions

Network quality	Digit Span			At least secondary education			Age		
Migration equation	Perm.	Temp.	Diff. [p-val]	Perm.	Temp.	Diff. [p-val]	Perm.	Temp.	Diff. [p-val]
Completed primary education	-0.019	-0.032	-0.013	0.028	-0.017	-0.044	-0.027	-0.053	-0.026
	(0.030)	(0.043)	[0.782]	(0.039)	(0.043)	[0.408]	(0.035)	(0.043)	[0.611]
× Migrant networks, tercile two	-0.007	0.096	0.104	-0.085	-0.002	0.083	-0.040	0.050	0.090
	(0.039)	(0.061)	[0.127]	(0.040)**	(0.053)	[0.158]	(0.046)	(0.069)	[0.254]
× Migrant networks, tercile three	-0.027	-0.008	0.018	-0.119	0.054	0.173	0.022	0.053	0.031
	(0.057)	(0.062)	[0.844]	(0.070)*	(0.073)	[0.079]	(0.069)	(0.075)	[0.765]
Complete secondary education	0.080	0.117	0.036	0.047	0.007	-0.040	0.017	0.127	0.110
	(0.076)	(0.075)	[0.693]	(0.062)	(0.051)	[0.617]	(0.071)	(0.058)**	[0.034]
× Migrant networks, tercile two	-0.042	-0.037	0.005	-0.050	0.077	0.127	-0.106	-0.128	-0.022
	(0.078)	(0.090)	[0.963]	(0.076)	(0.068)	[0.207]	(0.092)	(0.091)	[0.833]
× Migrant networks, tercile three	-0.187	-0.124	0.063	-0.187	0.050	0.238	-0.007	-0.105	-0.098
	(0.092)**	(0.097)	[0.640]	(0.082)**	(0.073)	[0.052]	(0.083)	(0.092)	[0.386]
Completed higher than secondary education	0.082	-0.043	-0.126	0.097	-0.121	-0.218	0.097	-0.025	-0.122
	(0.063)	(0.063)	[0.108]	(0.100)	(0.060)**	[0.086]	(0.069)	(0.057)	[0.120]
× Migrant networks, tercile two	0.053	0.079	0.026	-0.065	0.153	0.219	-0.140	0.045	0.184
	(0.071)	(0.097)	[0.801]	(0.109)	(0.100)	[0.193]	(0.095)	(0.098)	[0.136]
× Migrant networks, tercile three	-0.249	0.037	0.286	-0.265	0.128	0.393	-0.150	0.003	0.152
	(0.075)***	(0.073)	[0.005]	(0.116)**	(0.077)	[0.011]	(0.089)	(0.083)	[0.148]
Ability	-0.029	-0.049	-0.019	-0.017	0.052	0.069	0.012	0.065	0.052
	(0.071)	(0.046)	[0.824]	(0.043)	(0.044)	[0.286]	(0.041)	(0.040)	[0.258]
× Migrant networks, tercile two	-0.016	0.138	0.154	0.016	-0.028	-0.045	0.045	0.016	-0.030
	(0.080)	(0.050)***	[0.111]	(0.045)	(0.054)	[0.582]	(0.058)	(0.045)	[0.658]
× Migrant networks, tercile three	0.228	0.148	-0.081	0.193	0.059	-0.134	0.088	0.001	-0.087
	(0.076)***	(0.051)***	[0.382]	(0.053)***	(0.051)	[0.060]	(0.053)	(0.044)	[0.179]
Migrant networks, tercile two	0.003	-0.128	-0.131	-0.036	-0.246	-0.210	-0.019	-0.032	-0.013
	(0.111)	(0.091)	[0.291]	(0.103)	(0.097)**	[0.226]	(0.078)	(0.103)	[0.908]
Migrant networks, tercile three	-0.135	-0.007	0.128	0.054	-0.094	-0.148	-0.064	-0.084	-0.020
	(0.124)	(0.103)	[0.337]	(0.079)	(0.095)	[0.283]	(0.087)	(0.091)	[0.857]
R-squared	0.11	0.08		0.12	0.10		0.09	0.08	
F test p-val:									
Ability-network variables = 0	0.00	0.02		0.00	0.16		0.26	0.89	
Education-network variables = 0	0.00	0.66		0.03	0.66		0.32	0.67	

Source: Pakistani Panel Survey 1986–1991 (IFPRI 1991), PIDE 2001 (Nayab and Arif 2012), and Pakistani Panel Tracking Survey 2013–2014 (IFPRI 2014).

Note: KPK = Khyber Pakhtunkhwa; HH = household. Marginal effects presented. Standard errors in parentheses. *p< 0.1 ** p< 0.05; *** p< 0.01. P-values in brackets for statistical difference in coefficient estimates across models. The number of observations in the permanent and temporary migration regressions are 1,103 and 1,198, respectively. Specifications follow those estimated in Table 5.4, replacing the Digit Span (overall) score with the ability measures listed above. For brevity, only the coefficient and standard error estimates of the ability coefficients are reported.

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