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Temporary and permanent migrant selection: theory and evidence of ability-search cost dynamics*

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Abstract

We integrate two workhorses of the labor literature, the Roy and search models, to illustrate the implications of migration duration—specifically, whether it is temporary or permanent—for patterns of selection. Consistent with our stylized model, we show that temporary migrants are intermediately selected on education, with weaker selection on cognitive ability. In contrast, permanent migration is associated with strong positive selection on both education and ability, as it involves finer employee–employer matching and offers greater returns to experience. Networks are also more valuable for permanent migration, where search costs are higher. Labor market frictions explain observed network–skill interactions.

KEYWORDS

migration, networks, Pakistan, self-selection

JEL CLASSIFICATION

J61; O15

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1 | INTRODUCTION

As the geographic mobility of workers continues to rise, migration—the movement of individuals and families—will be as central to economic development as trade. Remittances now far exceed official aid flows (Ratha et al., 2014), and the skill composition of migrants has increasingly important consequences for destination markets (Card, 1990, 2005; Borjas, 2005, 2006; Ottaviano and Peri, 2012). But, unlike trade, individuals must move with their "goods," raising complex questions about both the motives and the scope for migration. To better understand the impact of migration on both spatial and economic inequality, we must consider more deeply the migration decision itself (Henderson, 2010; Young, 2014; Gollin et al., 2017).

The literature has extensively explored the profile of immigrants to inform policy-makers of potential shifts in labor force composition (Chiquiar and Hanson, 2005; Orrenius and Zavodny, 2005; McKenzie and Rapoport, 2010; Moraga, 2011, 2013; Bertoli et al., 2013; Kaestner and Malamud, 2014). Previous studies have focused heavily on immigration to the USA, but internal migration is an increasingly common form of migration worldwide.[1] Historically, internal migration has also been central to economic growth by reallocating rural labor to support the expansion of the urban manufacturing sector (Lewis, 1954). Yet the extant literature still largely fails to differentiate among migrants, despite drastically varied motives and skills (Rogerson, 1990; Newbold, 2001, 2012). The profile of internal migrants is of particular concern to the Pakistani government, given objectives to shift production away from resource-based exports to manufacturing-based exports (News, 2017).

In this paper we take an initial step toward modeling heterogeneity within internal migration by focusing on variation in the duration of migration episodes among individuals originating from the same areas and in the same time period. To formalize differences between permanent and temporary migration, we embed a classic Roy (1951) model with heterogeneous moving costs, as in previous work (Chiquiar and Hanson, 2005; McKenzie and Rapoport, 2010; Orrenius and Zavodny, 2005), into a standard search model (Lippman and McCall, 1976). Variation in the duration of migration opportunities implies important distinctions not only in the decision process but also in patterns of self-selection, resulting in differing effects on both origin and destination labor markets. For example, temporary migration can dampen business cycles by increasing labor supply when wages are high, while permanent migration can have the opposite effect if labor supply is slow to respond to changes in market conditions.[2]

We use data from a unique panel survey of rural households in Pakistan spanning 22 years (1991–2013) to study the drivers of selection into temporary and permanent internal migration. The data offer an array of detailed information on worker attributes including education, cognitive ability (digit span and Raven's test scores), and visible physical ability (height). Our empirical findings confirm stronger positive selection for permanent migrants than for temporary migrants with respect to formal schooling. However, networks play a nuanced role, both drawing high-ability types and dissuading the highly educated. This suggests that, while networks can reduce search costs, particularly for high-ability workers, there are limits to what they can do. Using an alternative data source (Pakistan Bureau of Statistics, 1991, 2002, 2013), we show that our findings on education are consistent with networks alerting highly educated workers of a low elasticity of demand for skilled labor at destinations.

The remainder of the paper is organized as follows. Section 2 presents our theoretical framework, describing the choice between migrating permanently, temporarily, or remaining at the origin. Section 3 describes our dataset, while Section 4 outlines our empirical approach. Sections 5 and 6 present our main results and robustness checks. Section 7 concludes.

2 | THEORETICAL FRAMEWORK

In this section we lay out a stylized search model, as in Lippman and McCall (1976), to illustrate 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 type of migration.[3]

2.1 | Search with permanent and temporary opportunities

Consider two different types of migration which can be, and often are, employed by different individuals in the same period or by the same individual in different periods.[4] The first involves a *permanent* employment opportunity and, with it, a permanent change of residence. This type of migration often occurs over longer distances and requires greater upfront investment (Kleemans, 2015). The second involves a *temporary* employment opportunity, necessitating a temporary change of residence and an eventual return to the origin. This type of migration often occurs over shorter distances, and is more frequently used as a short-term diversification or risk-coping mechanism, requiring relatively little upfront investment (Bryan et al., 2014). Migration is no longer a binary choice; in each period, the individual considers both opportunities and selects the one that maximizes expected life-time utility. Given differences between the two types of opportunities, different patterns of selection will emerge as well.

We formalize this choice process using a standard search model. We assume an individual faces a fixed working life, at the beginning of which he receives a lifetime wage offer in the tehsil (i.e. sub-district) of origin.[5] This operates much like unemployment insurance in labor search models, though the "benefits" in this case do not expire, and ensures that not everyone will choose to engage in permanent migration during their working life. Each individual also has employment opportunities outside of the home tehsil, some temporary and some permanent. For ease of exposition, we consider an extreme case where temporary employment episodes last only a single period, while permanent employment offers last for the remainder of the working life. However, the implications of the model do not hinge on the exact duration of temporary and permanent migration episodes. The key distinction is simply that permanent migration provides employment over a substantially longer period of time than does temporary migration.

A temporary employment opportunity is available in each period but for only a single period, akin to entering a spot market for labor at the destination. In this case, the individual observes a wage distribution for temporary employment opportunities that may vary from period to period.[6] The individual must then incur a search cost (i.e. move to the destination) in order to accept the temporary migration opportunity and obtain a specific wage draw. A permanent offer from outside the home tehsil can also be obtained in each period. Permanent employment provides a lifetime wage drawn from a known distribution. In this case, search costs must be incurred before the wage draw is received, consistent with the notion that permanent migrants often identify a (set of) specific employment opportunities before migrating.[7]

We assume that the individual maximizes expected discounted lifetime income, net of search costs, given the following choices in each period:[8] (1) work at home and do not search for another job; (2) work at home and search; (3) accept a temporary wage offer and do not search; (4) accept a temporary wage offer and search; or (5) accept a permanent wage offer. The individual may also recall (i.e. return to) any previous lifetime employment opportunity. Intuitively, a temporary offer will be accepted if the wage gains exceed the search cost (see the Appendix for details). A permanent wage offer will be accepted when the wage gains exceeds the continuation value.

The key motivation for distinguishing temporary and permanent migration is the differing behavior of reservation wages over time. For temporary migration, the individual simply evaluates earnings at home (or in another permanent job) relative to the distribution of earnings in the temporary employment market in each period, and the reservation wage is constant over time. 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. Given a finite time horizon, the expected benefit of continued search decreases over time (Lippman and McCall, 1976). Therefore, permanent migration becomes an optimal stopping problem rather than a single-shot choice.

2.2 | Self-selection

The solution to the model suggests that the likelihood of either temporary or permanent migration, conditional on having never previously migrated, depends only on the current wage draws (see the Appendix). Simply allowing for two opportunities that differ *ex ante* in duration yields several important implications on selection into different types of migration.

2.2.1 | Human capital

Empirically, the effect of skill on migration depends on both the effect of skill on the wage distribution and search costs, as well as the effect of the wage distribution and search costs on the migration decision. With both wages and search costs as functions of human capital, our model, like Chiquiar and Hanson (2005), can produce much richer patterns of skill-based selection than when ignoring the duration of moves.

Consider first temporary migration. The short duration of these work opportunities implies that there is typically insufficient time to realize the full returns to human capital and, therefore, a lower skill price occurs in the temporary migrant market than in the home market. Moreover, because the wage is available for only a single period, search costs must also be lower for temporary than for permanent migration (which offers lifetime employment), *ceteris paribus*. If search costs are too high for those at the lower tail of the skill distribution and temporary migrants receive lower returns to skill, then we will observe a nonlinear relationship between skill and migration. The lowest-skilled individuals will be excluded from migration by search costs, while the highest-skilled individuals will prefer to stay in the home market, which has higher returns to skill, resulting in a pattern of intermediate selection (Figure A1). Conversely, for permanent migration, individuals are seeking out better matches for their skills in other markets, implying that the returns to human capital should be higher for migration opportunities, compared to the home market. However, because more specialized matching is required, search costs will be higher than for temporary migration. In this case, we would observe strictly positive selection for permanent migration. Only the most highly skilled individuals would be able to overcome search costs, and all people above the skill cutoff will migrate because the returns to skill are also higher with migration.

2.2.2 | Search costs

As discussed above, differences in the duration of migration episodes imply differences in search costs as well. First, search costs must be higher for permanent than temporary moves, *ceteris paribus*, in order to observe both short- and long-term migration simultaneously. Second, longer employment contracts will require a higher degree of skill-based matching, again suggesting that search costs are increasing in the duration of migration episodes. Most importantly, the longer duration of permanent migration episodes increases the implicit cost of continued search. With a finite horizon, the value of continued search for permanent migration opportunities declines in each period, and this effect is compounded by search costs. In turn, this increases the likelihood that search is terminated before an acceptable offer is obtained.[9] In contrast, a favorable wage draw for temporary migration can, in any period, overcome search costs and induce migration, irrespective of history. Search costs, and the individual characteristics that influence those costs, will, therefore, have a larger effect on permanent migration.

2.2.3 | Reference period

The distinction between permanent and temporary migration additionally reveals that both the recall period and the age profile of respondents will affect observed patterns of migration. As the reservation wage for temporary migration offers is time invariant, inferences based on migration activity in a single period of time (e.g. the last five years) will yield similar results irrespective of which "snapshot" in time is taken. In contrast, the reservation wage for permanent offers decreases over time 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 effect of search costs. Thus, to accurately characterize permanent migration, data on lifetime migration are needed, particularly during the early adult years, when permanent migration is more likely.

To summarize, our model highlights how the duration of migration opportunities will influence both patterns of self-selection and the role of search costs. The implications are quite intuitive: longer migration opportunities create greater potential for skill-based matching, require more costly search efforts, and generate the need for dynamic optimization. In the empirical analysis, we explore how these factors affect permanent and temporary migration decisions in rural Pakistan.

3 | BACKGROUND AND DATA

3.1 | Migration in Pakistan

Pakistan is a middle-income, democratic country with the world's sixth largest population (Central Intelligence Agency, 2015), lending it considerable geopolitical importance. However, its poverty rate has declined extremely slowly in recent years, and is especially high in rural areas (Malik et al., 2016). Nonetheless, Pakistan is a relatively economically mobile country; for example, Corak (2012) finds that it has higher inter-generational mobility than the United States, the United Kingdom, Italy, and China.[10]

Pakistan is comprised of four main provinces (Punjab, Sindh, Khyber Pakhtunkhwa (KPK), and Balochistan), each further subdivided into three tiers of local government: districts, tehsils, and union councils. The provinces have considerable autonomy; for example, in 2010 the 18th Amendment to Pakistan's Constitution devolved 17 major federal ministries and many essential development responsibilities to the provinces (Shah, 2012). Districts also play an important role in governance, helping to identify development priorities and implement policies and investments.

As of 2013, 10 percent of those living in Pakistan were migrants—most (93 percent) of them internal (Pakistan Bureau of Statistics, 2013). The migration rate has declined by 3 percent over the last decade (Pakistan Bureau of Statistics, 2002). In a setting in which 63.5 percent of the population is rural (Malik et al., 2016), internal migrants were nearly evenly split between rural and urban destinations (Pakistan Bureau of Statistics, 2013). Internal migration in Pakistan is a driver of economic growth in key sectors including agriculture, manufacturing, construction, and services (Ishfaq et al., 2017). There are large development differentials both across and within provinces which have also contributed to extremely uneven access to public services (World Bank, 2014; Afzal et al., 2016). Policies governing internal migration and restricting or protecting internal migrants are virtually non-existent; neither the National Emigration Policy of 2009 nor the 2010 Labour Policy mentions internal migration (Ishfaq et al., 2017). These conditions could motivate internal migration.

3.2 | Data source

Our main source of data is a household survey carried out in Pakistan between September 2013 and July 2014 that tracked all individuals in a set of households last surveyed in 1991 as part of the International Food Policy Research Institute (IFPRI) Pakistan Panel Survey (PPS, 1986–91).[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 Punjab province), Badin (in Sindh province) and Lower Dir (in KPK province).

Using original (i.e. 1991) rosters of PPS households, the survey team completed a tracking roster documenting all original 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 the tracking rosters completed, a current household roster was completed 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 2013–14 PPTS with data from a tracking survey carried out in 2001 by the Pakistan Institute for Development Economics (PIDE; Nayab and Arif, 2012). This survey team visited each of the original 726 PPS households and noted whether each original PPS household member was present, not present but still considered a household member (i.e. temporarily away), or no longer a household member (i.e. permanently away). For those who were no longer members, they recorded whether their new location was in Pakistan or abroad. These data allow us to observe temporary migration not only at the endpoints of our surveys (1991 and 2013–14), but also in the middle of this period. Section 3.4 further details how we make use of these 2001 data, in precisely describing the particular definitions of temporary and permanent migration employed.

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 between age 0 and 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. We omit women as they almost uniformly migrate for reasons of marriage rather than employment, making their decisions less relevant from the standpoint of our model. The final sample consists of 1,346 adult men at risk of migrating during 1991–2013.

3.3 | Attrition

Figure 1 illustrates our tracking success rate for the 2013–14 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 other large panel surveys (Thomas et al., 2001). Excluding these two groups, 180 of 1,526 individuals attrited from the survey between 1991 and 2013–14—just under 12 percent. Tracking concluded prematurely in August 2014 due to security conditions in the field, which also prevented tracking of international migrants.[12]

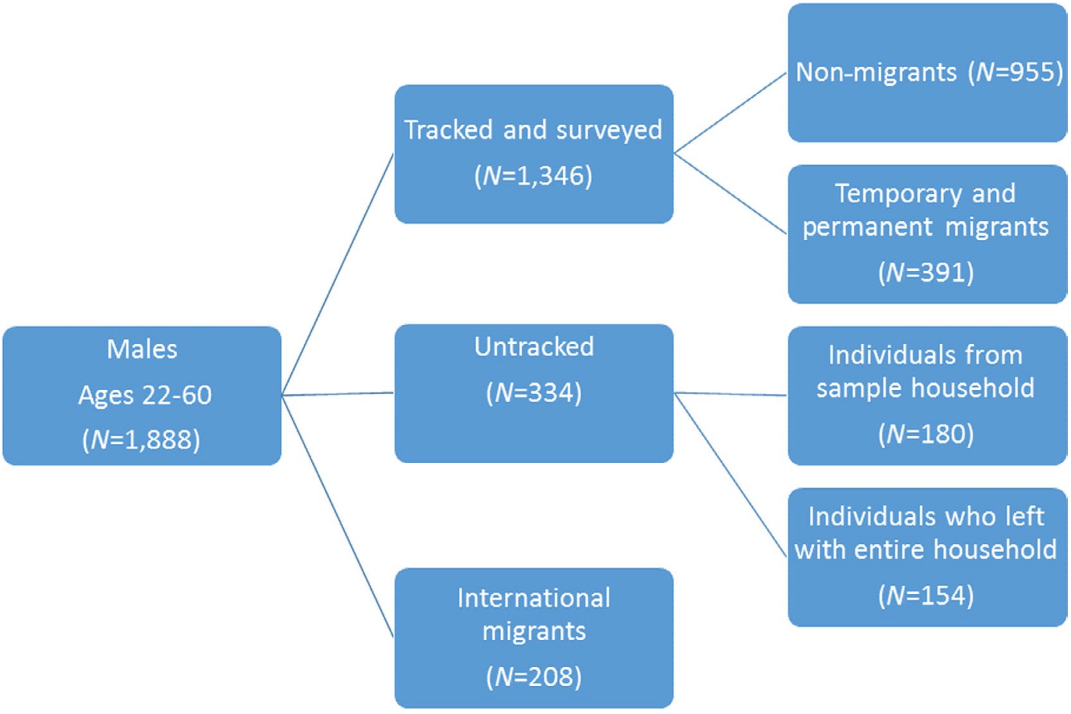

FIGURE 1 Pakistan panel tracking survey 2013–14 [Colour figure can be viewed at wileyonlinelibrary.com]

Individual attrition is of particular concern in the context of a migration study, as the majority of attritors are migrants as well. To gauge the severity of this problem, we report in Table A1 the 1991 characteristics of tracked and untracked respondents. We find few significant differences across groups, except that untracked respondents originate from slightly wealthier and better-educated households. In contrast, individuals who attrited along with their full household 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 household 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, 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 who could not be tracked, 124 (69 percent) were permanent migrants, 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 is consistent with permanent migrants traveling longer distances, both geographic and social. The tracking rate for temporary migrants is also higher because those who were reported as temporarily away in earlier survey rounds had returned by 2013–14, and did not require special tracking. 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 show that our results are robust to using inverse probability weights.

3.4 | Migration

Our primary interest lies in understanding differences in selection into permanent and temporary migration. Since we lack complete data on temporary migration histories, we focus on an individual's observed first move since 1991. As such, we divide individuals in our sample into three mutually exclusive, exhaustive categories: those that never migrate between 1991 and 2013–14, those whose observed first move was a temporary one (temporary migrants), and those whose observed first move was a permanent one (permanent migrants).[13] We do not observe the intended length of migration spells in our data and, moreover, intentions may change after migration has occurred. Our definition of temporary versus permanent is, therefore, based on the household's report of whether the individual remains a member. Permanent migrants are individuals no longer considered as belonging to the original PPS household and, because the entire history of permanent migration was collected, we include all moves following the 1991 survey up to the time of the 2013–14 PPTS. The majority of permanent migrants have never previously engaged in temporary migration. Although the primary motive for leaving the household is reported, we do not restrict our sample based on this information, as economic and marital migration decisions are often interlinked. We do, however, require a move to be out of the origin tehsil to be counted as migration. This helps us exclude moves within the same labor market.

We define temporary migration as an individual being temporarily away but still considered a PPS household member. We examine whether this occurred in each of the three survey waves: 1991, 2001, and 2013–14. In our model, the temporary migration decision is time invariant; the individual simply evaluates temporary migration opportunities against wages at the origin in each period, and both timing and prior migration history are irrelevant. Since the temporary migration decision is the same in each period, our results should not be affected by the choice of periods or by limiting our attention to only three periods. Basing our migration definitions on reported household membership better reflects expectations regarding the duration of migration and does not impose any (arbitrary) time constraints on temporary migration.[14] The requirement that temporary migrants still be considered members of the PPS household distinguishes them from permanent movers. The large majority of these migrants are observed later returning to the household but, 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 did not permanently leave the PPS household at the time of a subsequent survey.

About 10.9 percent of individuals in our sample are coded as permanent migrants and 18.1 percent are temporary migrants, based on the first migration episode.[15] The tracking rosters collected limited information about migrants' destinations, and we do not know the destinations of temporary migrants. However, since we administered a household survey to all permanent migrants and non-migrants in 2013–14, we can establish the destinations of permanent migrants. Permanent migrants are nearly equally split between moving within (47 percent) and across (53 percent) districts. Out-of-district migrants tend to move to districts containing cities with populations of over 1 million, such as Rawalpindi (23 percent), Karachi (12 percent), Lahore (10 percent), Gujranwala (8 percent), Faisalabad (6 percent), Peshawar (5 percent), and Islamabad (4 percent). The remaining 32 percent move to other districts.

3.5 | Education and ability

Expected wages and search costs are functions of human capital. To account for this, we include three categories of education: complete primary education, complete secondary education, and higher secondary or tertiary education, with no or less than primary education as the reference category.[16] In addition, we include the digit span z-score. This is based on the number of correct responses to eight forward and eight backward digit span questions. Respondents are provided a set of numbers and asked to repeat them in the same and/or opposite order. This tests an individual's attention, memory, and—for the backward digit span test—the higher-order cognitive ability of inverting the order of information.

There is a vast literature on the relationship between formal education and cognitive ability. While Herrnstein and Murray (2010) argue that education does not affect ability, Ceci and Williams (1997) describe a bidirectional relationship, and Banks and Mazzonna (2012) more recently exploit exogenous variation in the minimum school-leaving age to show large and significant effects of an additional year of education between ages 14 and 15 on men's ability at older ages. Education and ability are highly correlated in our sample, with a correlation coefficient of .40 between having tertiary education and one's digit span z-score. Nevertheless, by controlling for this measure of cognitive ability, we are better able to isolate the impact of formal education from underlying ability.

The overall digit span z-score is our primary measure of cognitive ability, but we examine the robustness of our results to several alternate measures, also converted into z-scores: digit span forward, digit span backward, standing height, and components of Raven's progressive matrices tests (Raven et al., 2000). Digit span forward has the virtue of being a measure of cognitive ability that is not adversely affected by illiteracy (Kosmidis et al., 2011)—a possible concern given that 31 percent of our sample for analysis have incomplete primary education. Height has been positively associated with both cognitive and non-cognitive ability (Vogl, 2014; Schick and Steckel, 2015) and may visually signal this ability. Finally, Raven test scores measure abstract reasoning; individuals are shown a series of patterns (i.e. matrices) and asked to select the missing element from a set of eight possibilities.

3.6 | Community networks and search costs

Community networks can reduce the costs of migration through the provision of housing, knowledge of labor market conditions, and referrals, among other factors (Carrington et al., 1996; Chau, 1997; Ndoen et al., 2002; Munshi, 2003; McKenzie and Rapoport, 2007, 2010). Following Massey et al. (1994) and McKenzie and Rapoport (2010), we measure an individual's community migration network using the share of all original 1991 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 since migrants of either gender—and individuals in their new households—may assist new migrants. This formulation of networks helps to mitigate simultaneity bias because, while it focuses on individuals from the same village, it incorporates migration activities from and to a variety of origin and destination points, spread over a long time period. As a result, networks are less likely to be correlated with either local economic conditions at the time of migration, or composition effects in the labor market driven by recent migration trends.

Search costs will also be affected by transportation costs and liquidity constraints. To account for the former, we include the distance of the PPS village to a primary (i.e. paved/high-quality) road in 1994—the closest year to 1991 for which we have data (Survey of Pakistan, 1994).[17] In select cases where we lack GPS coordinates, we assign the village to the centroid of its tehsil, computed from a map of tehsil boundaries (United Nations Office for the Coordination of Humanitarian Affairs and Peace Corps Organization, 2011) To account for the latter, we control for the value of durable (non-land and non-livestock) assets owned by the PPS household in 1991.[18] We exclude productive wealth (land and livestock) so that our measure primarily reflects liquidity rather than farm productivity.[19] Just over 5 percent of individuals in our estimation sample are household heads. Thus, for nearly 95 percent of individuals, this is a measure of the assets owned by their parents and family (i.e. initial wealth) rather than a measure of personal asset accumulation. We verify that our main findings are robust to excluding all household heads from the sample (Table A2). We divide assets into terciles following McKenzie and Rapoport (2007), who provide theoretical intuition for a nonlinear relationship between migration and household asset wealth.

4 | EMPIRICAL STRATEGY

Our main objective is to test how selection differs for permanent and temporary migrants. Relating this to our search model, our empirical approach estimates how individual characteristics differentially affect the reservation wages for temporary and permanent migration, similar to Kiefer and Neumann (1979), Wolpin (1987), and Blau (1991).[20] Recall that permanent and temporary are defined by the *first* observed migration episode and are, therefore, mutually exclusive. The comparison group in each case is individuals with no reported migration during the survey period. Migrant selection is modeled via a linear probability model with separate regressions for permanent and temporary migration:[21]

$$M^k_{ihl} = f(H_{ih};W_{ih};\pi_h;\alpha) + \gamma_l + \epsilon_{ihl}, \tag{1}$$

where M^k_{ihl} is an indicator for whether individual i in household h engaged in migration type k (temporary or permanent) from province l during 1991–2013. H_{ih} is a vector of human capital factors that influence the decision to migrate: individual age and education categorical variables; ability, our primary measure of interest being the digit span z-score; and the community migrant network, measured by tercile categorical variables for the share of all original PPS village members who migrated during 1991–2013 (excluding all members of the individual's household). W_{ih} is a measure of initial wealth; it includes tercile categorical variables for the value of durable assets in the individual's 1991 PPS household. It also captures the propensity to accumulate savings, as measured by an indicator for having ever been married and tercile categorical variables for the number of household members and child members in the 1991 PPS household. π_h represents transportation costs, proxied by tercile categorical variables indicating the distance from the household's community to a primary road in 1994. γ_l are province fixed effects.

Given the limited empirical work on this topic, our model allows for flexible relationships between human capital, wealth, and migration. We allow for potential complementarities between skills and search costs by including interactions between the migrant network variables and both the ability and education variables. For example, networks may be able to provide referrals that allow highly skilled workers to obtain better jobs (Beaman and Magruder, 2012). Migrant networks could also substitute for physical moving costs by conveying costly information about destination labor markets. To examine this, we include additional interactions between migrant networks and proximity to a primary road.

Our analysis is similar to that of Chiquiar and Hanson (2005) and Kaestner and Malamud (2014) in that our objective is to estimate self-selection into migration, here distinguishing by migration duration. Our regression framework allows us to examine selection on several dimensions while accounting for correlations between these factors. In interpreting our estimates, it should be noted that they capture patterns of selection rather than strictly causal effects. With little to no empirical evidence on how permanent and temporary migrants differ and to what extent, these descriptive patterns of selection are a necessary starting point, in order to understand how expanding opportunities for migration will affect the composition of migrant cohorts and impact destination economies. Similarly, understanding selection patterns is essential for estimating the impact of migration on origin communities and households.[22]

Summary statistics are presented in Table 1.[23] Individuals whose first observed migration episode is permanent are older than non-migrants, while the opposite is true for those who engage first in temporary migration. Both temporary and permanent migrants appear to have certain advantages

TABLE 1 Summary statistics

Variable	Non-migrant mean	Permanent migrant mean	Difference (*p*-value)	Temporary migrant mean	Difference (*p*-value)
Age 22–24	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 55–60	0.06	0.08	0.27	0.05	0.45
Incomplete primary education	0.34	0.28	0.13	0.21	0.00
Complete primary education but incomplete secondary	0.3	0.28	0.78	0.27	0.47
Complete secondary education	0.16	0.18	0.68	0.24	0.01
Complete 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 (1,000s rupees)	88.57	134.32	0.01	97.94	0.48
1991 household size	12.18	11.93	0.65	13.16	0.03
1991 No. child household 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's z-score (overall)	−0.07	0.09	0.08	0.16	0.00
Raven's z-score (A)	−0.05	0.18	0.01	0.21	0.00
Raven's z-score (B)	−0.06	0.04	0.24	0.12	0.01
Raven's 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	0.13	0.16	0.00	0.14	0.03
Digit span scores, 1991					
Community networks with secondary	0.09	0.11	0.00	0.11	0.00
or above completed education, 1991					

(Continues)

TABLE 1 (Continued)

Variable	Non-migrant mean	Permanent migrant mean	Difference (*p*-value)	Temporary migrant mean	Difference (*p*-value)
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	

for migration when compared with their non-migrant counterparts. They are, on average, closer to a primary road and have denser migrant networks than do non-migrants. Both migrant types also have higher cognitive scores than non-migrants. A greater proportion of temporary migrants has completed secondary or more education, compared to non-migrants. Among permanent migrants, we also find that a greater proportion have completed education beyond secondary school compared to non-migrants, but the proportion completing secondary school are comparable to non-migrants. Permanent migrants also come from households with greater asset wealth per capita, while the opposite is true for temporary migrants. Temporary migrants come from larger households, on average.[24]

5 | RESULTS

5.1 | Age profile

Table 2 provides ordinary least squares results from regressions of permanent (column 1) and temporary (column 2) migrant selection. The final column shows the difference in the estimated coefficients between columns 2 and 1.[25] The likelihood of permanent migration (as the first move) is higher for older age groups, consistent with the decreasing reservation wage in our model.[26] Interestingly, the oldest group in our sample (age 55–60) has the highest likelihood of permanent migration, and we see no evidence of "leveling off," which would occur if search for permanent wage offers ceased at some age below the upper bound of our sample (age 60). In contrast, we observe a flattening of the age profile for temporary migration. This is consistent with a decreasing marginal utility of wealth; individuals with more work experience will have accumulated greater wealth and, consequently, derive less utility from a temporary wage shock. Alternatively, this pattern could also be indicative of returns to experience at the origin, which would diminish the value of temporary migration over time. The estimated age effects, for both types of migration, are stable across specifications (see Section 6), suggesting minimal correlation between age and other regressors.

5.2 | Human capital

The digit span *z*-score, on its own, has no statistically significant effect on either temporary or permanent migration. In contrast, education has statistically significant and large effects on both temporary

TABLE 2 Migrant selection with network interactions

	(1) Permanent	(2) Temporary	(2) - (1) Difference
KPK province (1991)	−0.197***	−0.078	0.119
	(0.067)	(0.084)	
Sindh province (1991)	0.012	−0.076**	−0.088**
	(0.023)	(0.036)	
Age 25–34	0.087**	−0.064	−0.151**
	(0.040)	(0.050)	
Age 35–44	0.079**	−0.088	−0.166***
	(0.030)	(0.053)	
Age 45–54	0.084**	−0.077	−0.161**
	(0.033)	(0.059)	
Age 55–60	0.135**	−0.090	−0.225***
	(0.064)	(0.057)	
Ever married	−0.012	0.001	0.013
	(0.029)	(0.037)	
1991 household size, tercile 2	0.009	0.064	0.055
	(0.033)	(0.050)	
1991 household size, tercile 3	0.039	0.120**	0.081
	(0.057)	(0.058)	
1991 No. children in household, tercile 2	−0.023	0.007	0.030
	(0.040)	(0.038)	
1991 No. children in household, tercile 3	−0.039	−0.071	−0.032
	(0.060)	(0.056)	
1991 household assets, tercile 2	0.019	−0.028	−0.047
	(0.034)	(0.031)	
1991 household assets, tercile 3	0.029	0.036	0.007
	(0.042)	(0.039)	
Migrant networks, tercile 2	−0.027	−0.032	−0.005
	(0.103)	(0.079)	
Migrant networks, tercile 3	−0.019	0.010	0.029
	(0.103)	(0.103)	
Complete primary education	−0.014	−0.037	−0.023
	(0.029)	(0.038)	
× Migrant networks, tercile 2	−0.007	0.047	0.055
	(0.050)	(0.066)	
× Migrant networks, tercile 3	−0.050	0.022	0.072
	(0.071)	(0.070)	

(Continues)

TABLE 2 (Continued)

	(1) Permanent	(2) Temporary	(2) - (1) Difference
Complete secondary education	0.050	0.171***	0.121**
	(0.055)	(0.049)	
× Migrant networks, tercile 2	−0.109	−0.207***	−0.098
	(0.083)	(0.067)	
× Migrant networks, tercile 3	−0.093	−0.139	−0.046
	(0.070)	(0.091)	
Higher than secondary education	0.132*	−0.005	−0.137**
	(0.075)	(0.056)	
× Migrant networks, tercile 2	−0.182*	−0.043	0.139
	(0.106)	(0.072)	
× Migrant networks, tercile 3	−0.223**	0.031	0.254**
	(0.089)	(0.088)	
Digit span z-score	−0.008	0.027	0.035
	(0.052)	(0.035)	
× Migrant networks, tercile 2	0.034	0.038	0.004
	(0.074)	(0.045)	
× Migrant networks, tercile 3	0.147**	0.071*	−0.077
	(0.060)	(0.042)	
Dist. to primary road, tercile 2	−0.123	−0.043	0.081
	(0.109)	(0.208)	
× Migrant networks, tercile 2	0.065	0.033	−0.032
	(0.148)	(0.188)	
× Migrant networks, tercile 3	0.197	0.098	−0.099
	(0.134)	(0.206)	
Dist. to primary road, tercile 3	−0.270**	−0.053	0.218*
	(0.106)	(0.116)	
× Migrant networks, tercile 2	0.168	0.205	0.037
	(0.165)	(0.133)	
× Migrant networks, tercile 3	0.272**	0.104	−0.168
	(0.122)	(0.128)	
Constant	0.214**	0.272**	
	(0.094)	(0.111)	
R^2	.09	.08	
N	1,103	1,198	
F-test p-value: digit span–network variables = 0	.01	.23	
F-test p-value: education–network variables = 0	.14	.08	
F-test p-value: road–network variables = 0	.09	.48	

Notes: Standard errors in parentheses. $^*p < .1$, $^{**}p < .05$, $^{***}p < .01$.

and permanent migration. Consistent with Figure A1, we find intermediate selection for temporary migration and strictly positive selection for permanent migration, and this difference is statistically significant as well. Permanent migration draws only the most highly skilled workers who have completed some tertiary education, while temporary migration is attractive to workers with intermediate skills (those that have completed secondary education only). Having some tertiary education increases the likelihood of permanent migration by 13.2 percentage points, while having completed secondary education increases the likelihood of temporary migrating by 17.1 percentage points. Together, these estimates suggest that, conditional on innate cognitive ability, there may be substantive gains in migrant labor markets from formal education, with greater returns to tertiary education for opportunities with longer duration.

5.3 | Search costs

Geographic isolation substantially reduces the likelihood of permanent migration and has a much smaller effect on temporary migration, consistent with our model. Specifically, in the case of thin (first tercile) networks, residing in a location very far from a primary road (third tercile of distance) is associated with a statistically significantly lower probability of migrating permanently (−0.270). In contrast, for temporary migration, when networks are thin, the effect of being in the third tercile of distance to a primary road is not statistically significant, and is smaller in magnitude.[27] Assets owned by the 1991 PPS household do not significantly predict either type of migration. These estimates suggest that credit/liquidity constraints may not play a key role in migration decisions, conditional on other factors.[28]

Temporary migration alone is positively influenced by the 1991 PPS household size. One might expect larger households to facilitate migration, as this allows fixed migration costs to be spread over more people. However, this will only be the case if the origin household benefits from the migration decision. Temporary migration often generates substantial benefits for the origin household, given the relatively high likelihood of remittance receipts and eventual return of the migrant (Stark and Lucas, 1988). In contrast, the benefits of permanent migration usually accrue predominantly to the migrant. For example, a permanent migrant now in Faisalabad, interviewed as part of a qualitative data collection exercise in our study districts, noted, ‘I only send money if there is some big issue back in the village; I need to keep in view my own needs and status’ (Aftab, 2014). As a result, *ceteris paribus*, having more household members is less likely to influence the migration costs faced by the migrant.

5.4 | Migrant networks

We find that, on average, migrant networks have no significant effect on either permanent or temporary migration. However, the interactions between networks and other factors reveal a much more nuanced relationship. *F*-tests of the joint significance of the interactions between distance to roads and network variables (see Table 2) show significant substitution effects between network size and search costs for permanent migrant employment, though not for temporary. For those in the bottom tercile of networks, distance to a primary road has a significant negative effect on permanent migration. However, this adverse effect of geographic isolation is almost perfectly offset by the presence of dense (third tercile) networks, indicating that strong migrant networks can mitigate search costs to a large extent.

We do not find any significant effect of access to roads for temporary migration, though migrant networks appear to help offset search costs, as represented by distance to a primary road. As networks must be dense (third tercile) to mitigate the search costs associated with permanent migration, and only do so for those who are geographically most isolated, it seems that networks provide (costly) information about job opportunities—particularly for long-distance, permanent movers. In contrast, if networks primarily provided referrals, we would expect their impact on permanent migration to be uniform across locations, irrespective of transportation costs. Further, our estimates suggest that moderate networks are insufficient to mitigate search costs associated with permanent moves, and that networks do not significantly reduce search costs of permanent moves for the less geographically isolated.

Complementarities between networks and skill are strong and offer perhaps the most interesting motivation for empirically distinguishing between selection into temporary and permanent migration. As shown in Table 2, higher-ability individuals are more likely to engage in permanent migration, but only provided that they have access to dense (third tercile) migrant networks. Again, as shown by an F-test of joint significance of the digit span z-score and its interactions with networks, this effect is significantly larger in magnitude for permanent migration—which tends to entail greater returns to ability—than for temporary migration. Conditional on having a network size within the third tercile, a one-standard-deviation increase in ability increases the likelihood of permanent migration by 14.7 percentage points, compared to 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. This may be strategic behavior on the part of the network—an effort to safeguard network quality by providing costly job information and referrals only to high-ability workers. Alternatively, strong networks may provide information that only high-ability workers can utilize.

Interactions between education and networks are more complex. 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 interactions 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, *ceteris paribus*. But, if they also have access to moderate (second tercile) or dense (third tercile) networks, they are 5.0 and 8.1 percentage points 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.

Importantly, the results do not appear to be driven by networks simply proxying for a larger village or one with superior infrastructure (e.g. electricity, public transportation). Table A4 shows that controlling for historic village characteristics does not alter our key findings.[29] What emerges from these results is a nuanced role for networks in the search process. Without strong networks, ability has no significant effect on migration, while the opposite is true for education. Intuitively, these findings suggest that, while ability may be the main determinant of worker productivity, education is more easily observed by 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/dense networks assist in migration for high-ability workers, yet appear to deter the migration of highly educated workers.

The results offer interesting insights into 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 among highly educated workers. 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 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 the Pakistani Labour Force Surveys (Pakistan Bureau of Statistics, 1991, 2002, 2013). In Table 3 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 secondary education, while the probability of unemployment is significantly higher. Although studies describing the labor markets in Pakistan are limited, recent case studies suggest increased trends in attaining tertiary education in conjunction with over-qualification in occupational choices (Farooq et al., 2008; World Bank, 2013). This leads to low returns and high unemployment.

6 | ROBUSTNESS

6.1 | Inverse probability weighting

To examine how our results may be affected by selective attrition, we rerun our main specification using the inverse probability weights recommended by Fitzgerald et al. (1998). The weighted regression version of Table 2 is shown in Table A5. We estimate restricted and unrestricted (with supervisor indicators and village attrition rate as instruments) probit regressions to formulate inverse probability

TABLE 3 Mincerian wage and unemployment 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 55–60	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^2	.289	.016
N	36,351	90,561

Notes: District-clustered standard errors in parentheses. ***$p < .01$. District and year fixed effects included.

weights. Table A6 shows the unrestricted results. Inferences are similar when accounting for attrition, with the exception of the negative effect of being 35–44 years old gaining significance in the temporary migration regression. The weighted specification appears to improve the overall precision of the coefficient estimates with negligible consequences for interpretation.[30]

6.2 | Auxiliary specifications

Table A3 provides ordinary least squares results from regressions of permanent (columns 1–4) and temporary (columns 5–8) migrant selection, removing network interaction variables. Four regressions are presented using the permanent and temporary migrant outcomes, starting with inclusion of indicators for the province of the 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 1991 PPS household demographics, wealth level, and distance to a primary road (columns 3, 7). Finally, we add community migrant networks (columns 4, 8). The final column is the difference between columns 4 and 8.

The simple specifications mask the contribution of education to migration. According to the estimates in columns 4 and 8, those with secondary education are less likely to migrate permanently and more likely to migrate temporarily. However, the point estimates are imprecisely estimated and differences in the effects across outcomes are only weakly significant (*p*-value 0.11). Having some tertiary education is also negatively correlated with both forms of migration, but the correlations are rather imprecise and have magnitudes close to zero. The above correlations between education and migration are attenuated when the interaction variables are omitted. This is due to the fact that the estimates in the abbreviated model conflate two countervailing effects: the first is the positive impact of education on the returns to migration, while the second reflects the negative effect of the signals provided by the social network regarding job opportunities for skilled employment.[31] In contrast to the findings on education, the parsimonious specifications support the positive correlations between cognitive ability, having dense migrant networks, and the temporary and permanent migration of workers in Pakistan.

To check that our results are not driven by assumptions about the error term, we also estimate two separate logit regressions for temporary and permanent migration. The estimated coefficients are nearly identical to our main specification (Table A7). For completeness, we also present results for a multinomial logit with three outcomes: temporary migration, permanent migration, and (as baseline category) staying in the village (Table A8), which again produces nearly identical parameter estimates. The multinomial specification may be more efficient, though Agresti (2012) notes that the efficiency gain is likely to be minor when the most prevalent category is used as the baseline. Additionally, the two specifications may differ because the multinomial logit specification places constraints on the coefficients (i.e. the probability of permanent versus temporary migration is equal to the difference between the probabilities of permanent versus no migration and temporary versus no migration), whereas the two binary logits do not (Long and Freese, 2006). However, for specifications that include only categorical variables, these constraints hold automatically using either specification. Our variables are all defined in categories, but the addition of interactions generates small differences between the multinomial and binary logit specifications.

6.3 | Restricting to adult and migrant samples

As we lack comprehensive information on the reason for both temporary and permanent migration over the duration of the panel survey, a remaining concern is that the empirical findings on education are driven by a subpopulation of young migrants, moving for reasons unrelated to employment. By

TABLE 4 Migrant selection with network interactions, excluding under age 15 in 1991

	(1) Permanent	(2) Temporary	(2) - (1) Difference
Age 45–54	0.017	0.004	−0.013
	(0.035)	(0.040)	[0.768]
Age 55–60	0.063	−0.007	−0.071
	(0.056)	(0.049)	[0.083]*
Migrant networks, tercile 2	−0.061	0.018	0.079
	(0.099)	(0.084)	[0.566]
Migrant networks, tercile 3	−0.001	−0.085	−0.084
	(0.123)	(0.096)	[0.609]
Complete primary education	0.006	−0.063	−0.070
	(0.046)	(0.040)	[0.263]
× Migrant networks, tercile 2	−0.015	0.149	0.164
	(0.068)	(0.078)*	[0.109]
× Migrant networks, tercile 3	−0.126	0.108	0.234
	(0.081)	(0.087)	[0.097]*
Complete secondary education	0.177	0.167	−0.010
	(0.101)*	(0.057)***	[0.934]
× Migrant networks, tercile 2	−0.233	−0.182	0.050
	(0.122)*	(0.109)	[0.736]
× Migrant networks, tercile 3	−0.257	−0.045	0.212
	(0.133)*	(0.085)	[0.247]
Higher than secondary education	0.233	−0.094	−0.327
	(0.087)**	(0.096)	[0.021]**
× Migrant networks, tercile 2	−0.251	−0.096	0.156
	(0.118)**	(0.101)	[0.325]
× Migrant networks, tercile 3	−0.333	0.235	0.568
	(0.109)***	(0.130)*	[0.001]***
Digit span z-score	−0.081	0.054	0.135
	(0.069)	(0.058)	[0.085]
× Migrant networks, tercile 2	0.073	0.084	0.010
	(0.094)	(0.060)	[0.920]
× Migrant networks, tercile 3	0.214	0.073	−0.141
	(0.074)***	(0.058)	[0.100]
Dist. to primary road, tercile 2	−0.168	−0.130	0.038
	(0.110)	(0.258)	[0.893]
× Migrant networks, tercile 2	0.152	−0.152	−0.305
	(0.145)	(0.249)	[0.307]

(Continues)

TABLE 4 (Continued)

	(1) Permanent	(2) Temporary	(2) - (1) Difference
× Migrant networks, tercile 3	0.231	0.125	−0.106
	(0.157)	(0.252)	[0.735]
Dist. to primary road, tercile 3	−0.339	−0.138	0.202
	(0.122)***	(0.106)	[0.199]
× Migrant networks, tercile 2	0.171	0.091	−0.080
	(0.171)	(0.114)	[0.670]
× Migrant networks, tercile 3	0.363	0.083	−0.280
	(0.139)**	(0.106)	[0.113]
Constant	0.294	0.210	
	(0.139)**	(0.129)	
R^2	.11	.14	
N	571	611	
F-test p-value: digit span–network variables = 0	.01	.35	
F-test p-value: education–network variables = 0	.03	.00	
F-test p-value: road–network variables = 0	.08	.00	

Notes: Standard errors in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. Specifications follow those estimated in Table 2; some coefficients are suppressed for the sake of brevity.

having detailed migration histories on permanent migration, we can at least confirm that the lower and upper quartile values for migrant ages during their first permanent move are 22 and 34 years old, indicating that the individuals at risk of moving permanently in our sample are likely of labor market age. However, we have less detailed information about the precise year of temporary migration episodes and cannot make a similar assertion on migrants' age.

To examine whether the educational parameters are robust to the age composition of the sample, in Table 4 we restrict the sample to individuals who were at least 15 years old in 1991. Again, the results remain essentially unchanged with regard to sign and statistical significance. However, we do find a greater wedge between those with weak and strong migrant networks with regard to tertiary education. In particular, the point estimate on the interaction between having tertiary education and network size being in the third tercile becomes more negative and significant (from −0.18, significant at the 5 percent level, to −0.33, significant at the 1 percent level) in the permanent selection model. Similarly, we witness a greater positive (and now statistically significant) effect on the same coefficient in the temporary selection model. These two stronger (and opposite-signed) inferences cause us to reject the null hypothesis that the effects on the coefficient are equal ($p = 0.001$). This suggests our main specification is likely to provide conservative estimates of the correlations between migration, networks, and education.

To determine the relative importance of human capital and network characteristics among the migrant sample, in Table 5 we estimate a single linear probability model where the dependent variable is an indicator for permanent migration; it takes the value 1 (0) for a permanent (temporary) migrant. The sample size is substantively smaller, weakening our ability to detect statistically significant differences. The correlation between tertiary education in the absence of migrant networks and permanent migration remains positive, while its interaction with having a dense network (third tercile) remains

TABLE 5 Selection into permanent migration with network interactions, migrants only

	(1) Permanent migrant
Age 25-34	0.224
	(0.087)**
Age 35-44	0.249
	(0.093)**
Age 45-54	0.258
	(0.102)**
Age 55-60	0.374
	(0.139)**
Migrant networks, tercile 2	0.077
	(0.222)
Migrant networks, tercile 3	0.035
	(0.198)
Complete primary education	−0.008
	(0.172)
× Migrant networks, tercile 2	−0.037
	(0.198)
× Migrant networks, tercile 3	−0.093
	(0.218)
Complete secondary education	−0.073
	(0.137)
× Migrant networks, tercile 2	0.052
	(0.241)
× Migrant networks, tercile 3	−0.057
	(0.185)
Higher than secondary education	0.181
	(0.184)
× Migrant networks, tercile 2	−0.168
	(0.212)
× Migrant networks, tercile 3	−0.354
	(0.227)
Digit span *z*-score	0.018
	(0.068)
× Migrant networks, tercile 2	−0.111
	(0.112)
× Migrant networks, tercile 3	0.085
	(0.076)

(Continues)

TABLE 5 (Continued)

	(1) Permanent migrant
Dist. to primary road, tercile 2	−0.071
	(0.303)
× Migrant networks, tercile 2	0.027
	(0.306)
× Migrant networks, tercile 3	0.125
	(0.311)
Dist. to primary road, tercile 3	−0.297
	(0.143)**
× Migrant networks, tercile 2	−0.073
	(0.222)
× Migrant networks, tercile 3	0.308
	(0.152)**
Constant	0.367
	(0.193)*
R^2	.13
N	391
F-test p-value: digit span–network variables = 0	.14
F-test p-value: education–network variables = 0	.62
F-test p-value: road–network variables = 0	.23

Notes: Standard errors in parentheses. *$p < .1$, **$p < .05$, ***$p < .01$. Specifications follow those estimated in Table 2; some coefficients are suppressed for the sake of brevity.

negatively correlated with permanent migration. We continue to observe distance to a primary road in the absence of networks serving as a strong barrier to permanent migration, while having access to a large network offsets that effect. The insights into selection presented by this alternative specification are qualitatively similar to those from our main specification. However precision of the human capital effects is limited by sample size.

6.4 | Alternate measures of cognitive ability

We next replicate the basic permanent and temporary migration regressions with alternative measures of cognitive ability: forward digit span, backward digit span, and height (Table 6). The table displays the estimated parameters and standard errors for the ability, education, and network variables, suppressing coefficients on other controls due to space constraints. 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 height.[32] That results are similar when using digit span forward scores is particularly encouraging given research showing that this measure—unlike many others—is not highly correlated with literacy. Height—a measure of visual ability— does not predict either form of migration when controlling for education. This suggests that

TABLE 6 Migrant selection and alternative measures of cognitive ability: digit span forward, digit span backward, and height

Ability Measure	Digit span (overall)			Digit span (forward)			Digit span (backward)			Height		
Migration Equation	Perm.	Temp.	Diff.	Perm.	Temp.	Diff.	Perm.	Temp.	Diff.	Perm.	Temp.	Diff.
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)		(0.026)	(0.039)		(0.031)	(0.038)		(0.026)	(0.037)	
× Migrant networks, tercile 2	−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)		(0.049)	(0.068)		(0.050)	(0.067)		(0.049)	(0.071)	
× Migrant networks, tercile 3	−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)		(0.067)	(0.073)		(0.073)	(0.068)		(0.071)	(0.067)	
Complete 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)		(0.055)	(0.048)		(0.054)	(0.048)		(0.056)	(0.050)	
× Migrant networks, tercile 2	−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)		(0.081)	(0.068)		(0.077)	(0.066)		(0.070)	(0.072)	
× Migrant networks, tercile 3	−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)		(0.068)	(0.098)		(0.073)	(0.087)		(0.071)	(0.090)	
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)		(0.064)	(0.054)		(0.079)	(0.058)		(0.069)	(0.059)	
× Migrant networks, tercile 2	−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)		(0.093)	(0.070)		(0.103)	(0.075)		(0.079)	(0.075)	
× Migrant networks, tercile 3	−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)		(0.079)	(0.096)		(0.101)	(0.087)		(0.096)	(0.090)	
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)		(0.042)	(0.036)		(0.046)	(0.028)		(0.021)	(0.018)	
× Migrant networks, tercile 2	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)		(0.059)	(0.043)		(0.064)	(0.040)		(0.028)	(0.030)	

TABLE 6 (Continued)

Ability Measure	Digit span (overall)			Digit span (forward)			Digit span (backward)			Height		
Migration Equation	**Perm.**	**Temp.**	**Diff.**	**Perm.**	**Temp.**	**Diff.**	**Perm.**	**Temp.**	**Diff.**	**Perm.**	**Temp.**	**Diff.**
× Migrant networks, tercile 3	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)		(0.050)	(0.043)		(0.055)	(0.037)		(0.032)	(0.025)	
Migrant networks, tercile 2	−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)		(0.096)	(0.081)		(0.098)	(0.071)		(0.082)	(0.064)	
Migrant networks, tercile 3	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)		(0.100)	(0.106)		(0.104)	(0.098)		(0.105)	(0.101)	
R^2	.09	.08		.08	.08		.09	.08		.07	.07	
F-test *p*-value:												
Ability-Network Variables=0	.01	.23		.00	.33		.12	.04		.36	.98	
education–network variables = 0	.14	.08		.04	.15		.40	.04		.47	.09	

Notes: Standard errors in parentheses. $^*p < .1$, $^{**}p < .05$, $^{***}p < .01$. The numbers of observations in the permanent and temporary migration regressions are 1,103 and 1,198, respectively. Specifications follow those estimated in Table 2, 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.

nutrition and educational outcomes are likely jointly determined by the household (Vogl, 2014). It also insinuates that migrant labor markets do not reward ‘brawn’ over ‘brains’ (Pitt et al., 2012).

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 (i.e. backward digit span).

7 | CONCLUSION

We combine a search model with a Roy model to help formally distinguish two types of migrants: temporary and permanent. In doing so, we illustrate how the duration of migration episodes can influence self-selection and the skill composition of migrants. We then test the implications of the model using a unique panel dataset from rural Pakistan spanning 22 years if detailed migration information. We find substantial differences in the patterns of selection for temporary compared to permanent migrants. There is clear evidence of positive selection on skill among both types of migrants. However, tertiary education is a key predictor of permanent migration, while having a secondary education is the more important predictor for temporary moves. This is consistent with the idea that, because temporary migration opportunities are shorter in duration, there is less scope for skill-based matching and learning, resulting in relatively low returns to higher levels of education. Similarly, cognitive ability (as measured by a digit span test score), which is more difficult to observe than schooling, is a significant predictor only for permanent migration, and only when the individual has dense networks that can help facilitate employee–employer matching.

Our results suggest that differences in the duration of migration episodes can lead to different patterns of selection—even when considering the same population, within the same time period. Policies promoting temporary versus permanent migration can, therefore, have very different implications for the skill level of new immigrants. Moreover, the distinction between temporary and permanent may also be a key factor in explaining cross-sectional differences in immigrant selection.

The results also have important implications for how we consider mobility and its barriers in Pakistan. Irrespective of how migration is defined, mobility in Pakistan remains low relative to the mobility of working-age populations in other developing countries. The links between migration, education, and networks highlight that even the mobility of the highly educated is constrained by prevailing labor market conditions. Migrant networks in Pakistan deter highly educated workers from moving to distant labor markets, perhaps due to an overall shortage of skilled occupations and declining returns to tertiary education. A second formative barrier is search costs, particularly for permanent migration. In our empirical model, we find that strong networks nearly perfectly offset the negative impacts of geographic isolation on permanent migration. This also points to the need for scalable technological solutions to match employers with employees from remote areas (World Bank, 2013). Moreover, these impediments to mobility suggest that educational disparities between origin and destination communities may underlie persistent regional wage differences, particularly in labor markets that attract permanent migrants.

NOTES

[1] Globally, an estimated 763 million people are internal migrants, compared to 214 million international migrants—making internal migration over 3.5 times more common (United Nations, 2013).

[2] Differences in the characteristics of permanent and temporary migrants may also help explain inconsistent findings in the existing literature regarding the effect of remittances on household investment and well-being. Yang (2008) reviews the bodies of literature that find opposing remittance impacts on household welfare. For example, because permanent migrants do not plan to return to the origin, they likely have weaker preferences for, as well as limited ability to influence, how remittances are utilized.

[3] Dustmann and Gorlach (2016) lay out a rich model of temporary migration to analyze optimal duration and return migration, given differences in purchasing power, returns to and accumulation of human capital, and location preferences. In this framework, as in that of Thom (2010), individuals make short-term migration choices in each period, and temporary migration can effectively become permanent under certain conditions. Our model differs in that we consider the choice between temporary and permanent moves *ex ante*. This assumption could be relaxed to allow for uncertainty in the duration of migration episodes *ex ante* by incorporating transitions between temporary and permanent migration (e.g. temporary migrants have lower search costs for permanent employment at the current destination, permanent migrants return home and/or resume search for other permanent migration opportunities). This would, undoubtedly, better approximate the richness of actual migration experiences. We abstract from uncertainty about migration duration and focus on temporary and permanent migration as distinct opportunities in order to highlight the circumstances under which the individual makes either a short- or long-term (though non-binding) decision to remain in a given labor market.

[4] Destination choice is not considered explicitly here.

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

[6] This specification allows for wage shocks as a motive for temporary migration without having to specify a stochastic process for wages.

[7] This assumption could easily be relaxed by allowing for some uncertainty about wage draws that is only resolved upon migration. Indeed, many permanent migrants may have imperfect information about opportunities at the destination (McKenzie et al., 2013), though this does not lessen the need to expend search costs prior to migration. A qualitative study conducted in our sample villages in 2014 confirms that migrants tend to move permanently only after securing a contract or establishing their business at the destination, while temporary migrants are more typically pulled into short-term contracting in construction or agriculture to satisfy local labor constraints (Aftab, 2014).

[8] See the Appendix for the associated value functions.

[9] Because search costs for permanent migration are sunk, higher costs lead search to conclude sooner, either by accepting a lower/earlier offer or by terminating the search process altogether. However, since the probability of permanent migration is deterministically zero after the search is terminated, the latter effect dominates, and the likelihood of permanent migration is net decreasing in search costs.

[10] Here, mobility refers to how predictive a father's income level is of the income level of his children.

[11] The PPS was carried out in 14 rounds over a period of 5 years. The survey originated in rural villages, but the geographic landscape changed over the last 22 years particularly in Punjab and Sindh where some villages are now considered peri-urban. We compared the age distribution, marital status, and completion of primary education of males in our sample to similar statistics collected by the 2013–14 Labour Force Survey. Our sample appears to be over-representative of the working-age population (15–65) in all provinces, ranging from an additional 33 to 38 percentage points. We also over-represent those having primary school completion in the Punjab and Sindh provinces by 19 and 13 percentage points, respectively.

[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.

[13] Individuals may have migrated temporarily or permanently before 1991. Since our sampling frame is based on the 1991 roster, our migration definitions focus on the first move observed for a person between 1991 and 2013–14.

[14] In practice, many surveys exclude from the household roster any individuals who have been away for more than 6 or 12 months, excluding some temporary migrants by default.

[15] Pakistani Labour Force Survey (LFS) data reveal that approximately 2 percent of males age 22–60 report being “temporarily away” in the last 12 months, compared to 18 percent of our sample that have temporarily migrated in at least one of three time periods. Thus, our measure does not appear to under-count temporary migrants. Our measure, however, is

likely to be somewhat higher than that in the LFS, as we include those who were reported as being "temporarily" away at the time of each survey, even if they had left more than 12 months ago.

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.

17 While 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).

18 Durable assets include the following: television/VCR; radio/phonograph/cassette player; bicycle/motorcycle; vehicles (car, truck, pick-up, bus); sewing machine/washing machine; refrigerator/cooler; jewelry/ornaments/watches; camera; guns; house/building; inventory for shops/crafts; and other.

19 Although livestock is often used as a form of self-insurance in developing countries (Ray, 1998), we exclude livestock as a covariate in our empirical model. Twenty percent of our sample was missing information on household livestock assets in 1991. Furthermore, we found that there were no statistically significant associations between either form of migration and livestock asset terciles (results available upon request). Livestock and durable asset terciles are not highly correlated. This may be a function of the transformation of communities in our sample since 1991 from primarily rural to peri-urban areas.

20 To estimate the direct effect of labor market opportunities on migration within the context of a search model, we would need data on search behavior and wage draws over an individual's entire working life.

21 We present binary and multinomial logit specifications in Section 6.2. The coefficient estimates are virtually identical, nor do we find any significant improvement in efficiency. Therefore, we focus on the linear probability specification for ease of interpretation.

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

23 All tables that use information from the panel household survey use data from the PPS (1991), PIDE (2001), and PPTS (2013–14). All variables specified in these tables come from the PPTS (2013–14) survey unless indicated otherwise.

24 Employment opportunities for permanent versus temporary migrants may attract workers with different skills given the qualifications required to fulfill short-term versus long-term jobs. Table 1 indicates that temporary migrants are more likely to engage in farming than permanent migrants. Permanent migrants are more likely to be wage earners than temporary migrants.

25 More parsimonious specifications are shown in Table A3 and discussed in Section 6.2.

26 Given the survey design, we cannot distinguish age and cohort effects.

27 Furthermore, the difference between the coefficients across models is statistically significant at the 10 percent level.

28 Alternatively, the relaxation of liquidity constraints may be offset by the relative appeal of staying with/near a wealthier household. It could also be the case that our measure of asset wealth is a poor proxy for the resources used to fund migration. In an alternate specification, we instead use landholdings as our measure of assets, and it was similarly uncorrelated with the probability of migrating permanently or temporarily. These results are available upon request.

29 We use data from the earliest year available in PPS (1986–91) community surveys on the following village characteristics: village has electricity (1989), village has public transportation (1989), unskilled male wages (rupees per day, 1986–7 average), village population (1986), percentage of households owning land (1986), percentage of village population who are artisans (1991), and percentage of land that is uncultivated (1991).

30 We also provide regression estimates including untracked migrants. However, for untracked individuals, we lack two explanatory variables: education and digit span. Our estimates remain reasonably stable (available upon request) once attritors are included but, given the importance of human capital in migration decisions, these results should be interpreted with caution.

31 A similar argument can be made for the statistically insignificant correlations between distance to primary roads and migration in the specification omitting the interaction variables. The negative impact of distance to primary roads offsets the positive impact of social networks, given their ability to reduce search costs, attenuating the coefficients toward zero.

[32] The interaction effect was also not significant when using the measures from Raven's test (available upon request). 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 Raven's 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's test 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.

REFERENCES

Aftab, S. (2014). Pakistan Rural Household Tracking Study—Qualitative Component. Consultancy Report for the International Food Policy Research Institute, Islamabad, Pakistan.

Afzal, M., G. Gajate-Garrido, B. Holtemeyer, and K. Kosec (2016). Public service delivery for rural development. In D. Spielman, S. Malik, P. Dorosh, and N. Ahmed (Eds.), *Agriculture and the rural economy in Pakistan: Issues, outlooks, and policy priorities*. Philadelphia: University of Pennsylvania Press.

Agresti, A. (2012). *Categorical data analysis*. Hoboken, NJ: Wiley.

Banks, J. and F. Mazzonna (2012). The effect of education on old age cognitive abilities: Evidence from a regression discontinuity design. *Economic Journal 122*(560), 418–448.

Beaman, L. and J. Magruder (2012). Who gets the job referral? Evidence from a social networks experiment. *American Economic Review 102*(7), 3574–3593.

Bertoli, S., J. Fernandez-Huertas Moraga, and F. Ortega (2013). Crossing the border: Self-selection, earnings and individual migration decisions. *Journal of Development Economics 101*, 75–91.

Blau, D. (1991). Search for nonwage job characteristics: A test of the reservation wage hypothesis. *Journal of Labor Economics 9*, 186–205.

Borjas, G. (2005). The labor-market impact of high-skill immigration. *American Economic Review 95*(2), 56–60.

Borjas, G. (2006). Native internal migration and the labor market impact of immigration. *Journal of Human Resources 41*(2), 221–258.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014). Under-investment in a profitable technology: The case of seasonal migration in Bangladesh. *Econometrica 82*(5), 1671–1748.

Calvo-Armengol, A. (2004). Job contact networks. *Journal of Economic Theory 115*, 191–206.

Card, D. (1990). The impact of the Mariel Boatlift on the Miami labor market. *Industrial and Labor Relations Review 43*(2), 245–257.

Card, D. (2005). Is the new immigration really so bad? *Economic Journal 115*(507), F300–F323.

Carrington, W., E. Detragiache, and T. Vishwanath (1996). Migration with endogenous moving costs. *American Economic Review 86*(4), 909–930.

Ceci, S. J. and W. M. Williams (1997). Schooling, intelligence, and income. *American Psychologist 52*(10), 1051.

Central Intelligence Agency (2015). *The world factbook 2013–14*. Washington, DC: Author.

Chau, N. (1997). The pattern of migration with variable migration cost. *Journal of Regional Science 37*(1), 35–54.

Chiquiar, D. and G. Hanson (2005). International migration, self-selection, and the distribution of wages: Evidence from Mexico and the United States. *Journal of Political Economy 113*(2), 239–281.

Corak, M. (2012). Economic mobility across the generations in the United States: Comparisons, causes, and consequences. Written Testimony to the United States Senate, Committee on Finance July 10th, 2012 Hearing on “Tax Reform: Drivers of Intergenerational Mobility and the Tax Code." *http://www.finance.senate.gov/imo/media/doc/Corak%20Testimony.pdf*.

Dustmann, C. and J.-S. Gorlach (2016). The economics of temporary migrations. *Journal of Economic Literature 54*, 98–136.

Farooq, S., U. Ahmed, and R. Ali (2008). Education, underemployment, and job satisfication. *Pakistan Journal of Commerce and Social Sciences 1*, 83–91.

Fitzgerald, J., P. Gottschalk, and R. Moffitt (1998). An analysis of sample attrition in panel data. *Journal of Human Resources 33*(2), 251–299.

Fry, A. and S. Hale (1996). Processing speed, working memory, and fluid intelligence: Evidence for a developmental cascade. *Psychological Science 7*(4), 237–241.

Gollin, D., M. Kirchberger, and D. Lagakos (2017). *In search of a spatial equilibrium in the developing world*. (NBER Working Paper No. 23916).. Cambridge, MA: National Bureau of Economic Research.

Henderson, J. V. (2010). Cities and development. *Journal of Regional Science 50*, 515–540.

Herrnstein, R. J. and C. Murray (2010). *Bell curve: Intelligence and class structure in American life*. New York: Simon and Schuster.

Ishfaq, S., V. Ahmed, and D. Hassan (2017). Internal migration and labour mobility in Pakistan. In I. Rajan (Ed.), *South Asia Migration Report 2017: Recruitment, remittances, and reintegration*. Chapter 12, pp. 321–342. London: Routledge.

Jaeggi, S., M. Buschkuel, J. Jonides, and W. Perrig (2008). Improving fluid intelligence with training on working memory. *Proceedings of the National Academy of Sciences of the USA 105*(19), 6829–6833.

Kaestner, R. and O. Malamud (2014). Self-selection and international migration: New evidence from Mexico. *Review of Economics and Statistics 96*(1), 78–91.

Kiefer, N. and G. Neumann (1979). An empirical job-search model, with a test of the constant reservation-wage hypothesis. *Journal of Political Economy 87*, 89–107.

Kleemans, M. (2015, December). Migration choice under risk and liquidity constraints. https://drive.google.com/file/d/0B4ErMVWubYvUU1Yb1F6amYxVTg/view

Kosmidis, M. H., M. Zafiri, and N. Politimou (2011). Literacy versus formal schooling: Influence on working memory. *Archives of Clinical Neuropsychology 26*(7), 575–582.

Lewis, A. (1954). Economic development with unlimited supplies of labor. *Manchester School 22*(2), 139–191.

Lippman, S. and J. McCall (1976). The economics of job search: A survey. *Economic Inquiry 14*(2), 155–189.

Long, J. S. and J. Freese (2006). *Regression models for categorical dependent variables using Stata*. College Station, TX: Stata Press.

Malik, S., H. Nazli, E. Whitney, A. Shahzad, and A. Mehmood (2016). Food, agriculture and rural development in pakistan. In D. Spielman, S. Malik, P. Dorosh, and N. Ahmed (Eds.), *Agriculture and the rural economy in Pakistan: Issues, outlooks, and policy priorities*. Philadelphia: University of Pennsylvania Press.

Massey, D., L. Goldring, and J. Durand (1994). Continuities in transnational migration: An analysis of nineteen Mexican communities. *American Journal of Sociology 99*(6), 1492–1533.

McKenzie, D., J. Gibson, and S. Stillman (2013). A land of milk and honey with streets paved with gold: Do emigrants have over-optimistic expectations about incomes abroad? *Journal of Development Economics 102*, 116–127.

McKenzie, D. and H. Rapoport (2007). Network effect and the dynamics of migration and inequality: Theory and evidence from Mexico. *Journal of Development Economics 84*(1), 1–24.

McKenzie, D. and H. Rapoport (2010). Self-selection patterns in Mexico-U.S. migration: The role of migration networks. *Review of Economics and Statistics 92*(4), 811–821.

Moraga, J. F.-H. (2011). New evidence on emigrant selection. *Review of Economics and Statistics 93*(1), 72–96.

Moraga, J. F.-H. (2013). Understanding different migrant selection patterns in rural and urban Mexico. *Journal of Development Economics 103*, 182–201.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the US labor market. *Quarterly Journal of Economics 118*(2), 549–599.

Nayab, D. and G. Arif (2012). *Pakistan Panel Household Survey sample size, attrition and socio-demographic dynamics*. (Poverty and Social Dynamics Paper Series 2012:01). Islamabad: Pakistan Institute of Development Economics.

Ndoen, M., K. Gorter, P. Nijkamp, and P. Rietveld (2002). Entrepreneurial migration and regional opportunities in developing countries. *Annals of Regional Science 36*, 421–436.

Newbold, K. (2001). Counting migrants and migrations: Comparing lifetime and fixed-interval return and onward migration. *Economic Geography 77*(1), 23–40.

Newbold, K. (2012). Migration and regional science: Opportunities and challenges in a changing environment. *Annals of Regional Science 48*, 451–468.

News (2017). Pakistan needs migration from resources-based production. *The News*, 29 July.

Orrenius, P. and M. Zavodny (2005). Self-selection among undocumented immigrants from Mexico. *Journal of Development Economics 78*(1), 215–240.

Ottaviano, G. and G. Peri (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association 10*(1), 152–197.

Pakistan Bureau of Statistics (1991). *Labour Force Survey, 1990–1991*. Islamabad: Author.

Pakistan Bureau of Statistics (2002). *Labour Force Survey, 2001–2002*. Islamabad: Author.

Pakistan Bureau of Statistics (2013). *Labour Force Survey, 2012–13*. Islamabad: Author.

Pitt, M., M. R. Rosenzweig, and N. Hassan (2012). Human capital investment and the gender division of labor in a brawn-based economy. *American Economic Review 102*(7), 3531–3560.

Ratha, D., S. De, E. Dervisevic, C. Eigen-Zucchi, S. Plaza, H. Wyss, S. Yi, and S. Reza Yousefi (2014). *Migration and remittances: Recent developments and outlook*. (Migration and Development Brief 22). Washington, DC: World Bank.

Raven, J., J. C. Raven, and H. Court (2000). *Manual for Raven's progressive matrices and vocabulary scales*. San Antonio, TX: Pearson.

Ray, D. (1998). *Development economics*. Princeton, NJ: Princeton University Press.

Rogerson, P. (1990). Migration analysis using data with time intervals of differing widths. *Papers in Regional Science 68*, 97–106.

Roy, A. (1951). Some thoughts on the distribution of earnings. *Oxford Economics Papers 3*, 135–146.

Schick, A. and R. Steckel (2015). The contributions of cognitive and noncognitive ability. *Journal of Human Capital 9*(1), 94–115.

Shah, A. (2012). The 18th Constitutional Amendment: Glue or solvent for nation building and citizenship in Pakistan? *Lahore Journal of Economics 17*(Special Edition), 387–424.

Stark, O. and R. E. B. Lucas (1988). Migration, remittances, and the family. *Economic Development and Cultural Change 46*, 465–481.

Survey of Pakistan (1994). www.surveyofpakistan.gov.pk.

Thom, K. (2010, August). Repeated circular migration: Theory and evidence from undocumented migrants. Rewtrieved from https://economics.uwo.ca/chcp/2011%20Workshop/Kevin_Thom.pdf.

Thomas, D., E. Frankenberg, and J. Smith (2001). Lost but not forgotten: Attrition and follow-up in the Indonesia Family Life Survey. *Journal of Human Resources 36*(3), 556–592.

United Nations (2013). *Cross-national comparisons of internal migration: An update on global patterns and trends* (Technical Paper No. 2013/1). New York: Author.Retrieved from https://www.un.org/en/development/desa/population/publications/pdf/technical/TP2013-1.pdf

United Nations Office for the Coordination of Humanitarian Affairs and Peace Corps Organization (2011). *Pakistan: Administrative level 3 (tehsil) boundaries*. Geneva: Global Administrative Unit.

Vogl, T. (2014). Height, skills, and labor market outcomes in Mexico. *Journal of Development Economics 107*, 84–96.

Wolpin, K. (1987). Estimating a structural search model: The transition from school to work. *Econometrica 55*, 801–817.

World Bank (2013). *World development report: Jobs*. Washington, DC: Author.

World Bank (2014). *Global economic prospects: Shifting priorities, building for the future*. Washington, DC: Author.

Yang, D. (2008). International migration, remittances, and household investment: Evidence from Philippine migrants' exchange rate shocks. *Economic Journal 118*(2), 591–630.

Young, A. (2014). Inequality, the urban-rural gap and migration. *Quarterly Journal of Economics 129*, 939–993.

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APPENDIX

THEORETICAL MODEL

Optimization problem. The individual faces a fixed working life, taken as given, of length N. At $t = 0$, the individual receives a lifetime wage offer w_0 in his or her tehsil (i.e. sub-district) of origin—the 'home' wage. In each period $t > 0$, an individual considers the following employment options. A temporary employment opportunity with wage w_s is available in each period but for only a single period.

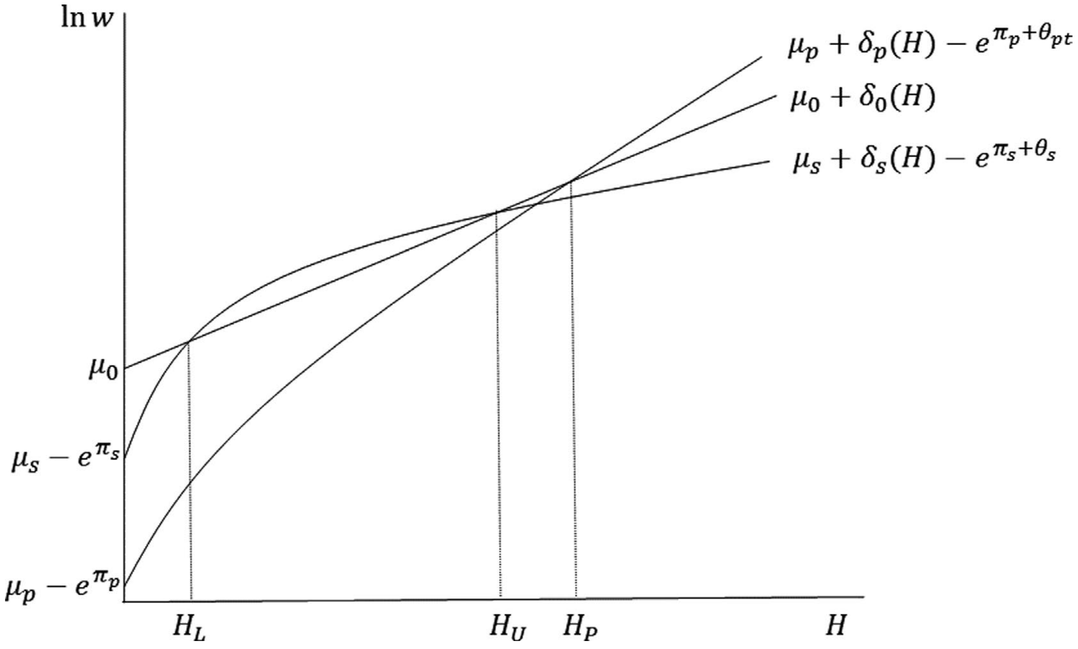

FIGURE A1 Migrant selection

TABLE A1 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	3.49	4.31	0.04	1.25	0.00
1991 number of children	5.48	5.23	0.49	6.86	0.00
1991 household size	12.70	12.12	0.29	13.03	0.56
1991 durable assets (1,000s 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	

The individual observes not a specific wage but a cumulative distribution for temporary employment opportunities $G_t(\cdot)$. This distribution may vary from period to period, with the mean of these temporary wage distributions drawn from a known distribution function $\Gamma(\cdot)$. A search cost c_s (i.e. moving to the destination) must be incurred in order to accept the temporary migration opportunity and obtain a specific wage draw. A permanent, lifetime wage offer w_p from outside the home tehsil can also be obtained in each period $t{+}1 \in \{1,N\}$. This is drawn from a known distribution with cumulative distribution function $F(\cdot)$ and can only be received after search costs c_p have been expended.

We assume that the individual maximizes expected discounted lifetime income, net of search costs, given the following choices in each period: (1) work in the home tehsil and do not search; (2) work

TABLE A2 Migrant selection with network interactions, excluding 1991 household heads

	(1) Permanent	(2) Temporary	(2) – (1) Difference
Age 25–34	0.086**	−0.064	−0.150**
	(0.039)	(0.049)	
Age 35–44	0.079**	−0.088*	−0.167***
	(0.030)	(0.052)	
Age 45–54	0.085**	−0.070	−0.155**
	(0.032)	(0.060)	
Age 55–60	0.198**	−0.086	−0.284***
	(0.080)	(0.063)	
Migrant networks, tercile 2	−0.054	−0.037	0.017
	(0.106)	(0.083)	
Migrant networks, tercile 3	−0.031	0.013	0.043
	(0.105)	(0.103)	
Complete primary education	−0.003	−0.029	−0.027
	(0.029)	(0.042)	
× Migrant networks, tercile 2	−0.010	0.044	0.054
	(0.052)	(0.071)	
× Migrant networks, tercile 3	−0.063	0.018	0.081
	(0.077)	(0.076)	
Complete secondary education	0.047	0.173***	0.126**
	(0.059)	(0.050)	
× Migrant networks, tercile 2	−0.090	−0.200***	−0.110
	(0.088)	(0.068)	
× Migrant networks, tercile 3	−0.104	−0.171**	−0.068
	(0.074)	(0.084)	
Higher than secondary education	0.139**	−0.000	−0.140**
	(0.075)	(0.058)	
× Migrant networks, tercile 2	−0.168	−0.039	0.129
	(0.104)	(0.082)	
× Migrant networks, tercile 3	−0.236**	0.016	0.252**
	(0.092)	(0.088)	
Digit span *z*-score	−0.025	0.026	0.052
	(0.048)	(0.037)	
× Migrant networks, tercile 2	0.048	0.035	−0.013
	(0.070)	(0.047)	
× Migrant networks, tercile 3	0.166***	0.074*	−0.092
	(0.058)	(0.043)	

(Continues)

TABLE A2 (Continued)

	(1) Permanent	(2) Temporary	(2) – (1) Difference
Dist. to primary road, tercile 2	-0.245^{**}	-0.015	0.230
	$(0.109)^{**}$	(0.233)	
× Migrant networks, tercile 2	0.192	0.005	-0.187
	(0.145)	(0.214)	
× Migrant networks, tercile 3	0.317^{**}	0.060	-0.256
	(0.135)	(0.230)	
Dist. to primary road, tercile 3	-0.303^{***}	-0.056	0.246^{*}
	(0.103)	(0.117)	
× Migrant networks, tercile 2	0.203	0.232	0.029
	(0.164)	(0.142)	
× Migrant networks, tercile 3	0.306^{**}	0.120	-0.187
	(0.124)	(0.135)	
Constant	0.235^{**}	0.270^{**}	
	(0.095)	(0.111)	
R^2	.09	.08	
N	1,044	1,136	
F-test p-value: digit span–network variables = 0	.01	.21	
F-test p-value: education–network variables = 0	.24	.12	
F-test p-value: road–network variables = 0	.16	.46	

Notes: Standard errors in parentheses. $^*p < .1$, $^{**}p < .05$, $^{***}p < .01$. Specifications follow those estimated in Table 2; some coefficients are suppressed for the sake of brevity.

in the home tehsil and search; (3) accept a temporary wage offer and do not search; (4) accept a temporary wage offer and search; or (5) accept a permanent wage offer. While in each job, he may also choose whether or not to search for another job. The individual may also recall (return to) any previous lifetime employment opportunity. Then, in each period $t > 0$, an individual considers the following value functions for home (0), permanent (p) or temporary (s, for a single period) employment:

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, $w_0-c_p+\beta(1-F(w_p))E\{\varphi(w,t+1)|w \geq w_p\}+\beta F(w_p)\varphi(w_p,t+1)$;
3. accept a temporary wage offer and do not search, $E[w_s]-c_s+\beta\varphi(w_p,t+1)$;
4. accept a temporary wage offer and search, $E[w_s]-c_s-c_p+\beta(1-F(w_p))E\{\varphi(w,t+1)|w \geq w_p\}+\beta F(w_p)\varphi(w_p,t+1)$;
5. accept a permanent wage offer, $w_p+\beta\vartheta(w_p,t+1)$.

Here 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.

Solution. The conditions for which a temporary or permanent migration offer will be accepted are derived by comparing the value functions above. A temporary wage offer will be accepted when

TABLE A3 Migrant selection without network interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8) - (4)
	Permanent Migration				Temporary Migration				Difference
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)	
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)*	
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)	
Age 55–60		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)*	
Migrant networks, tercile 2				0.017				0.033	0.016
				(0.039)				(0.051)	
Migrant networks, tercile 3				0.082				0.106	0.023
				(0.042)*				(0.046)**	
Complete 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)	
Complete 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)	
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)	
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)***	
Dist. to primary road, tercile 2			0.021	0.050			−0.004	0.031	−0.020
			(0.050)	(0.048)			(0.082)	(0.078)	
Dist. to primary road, tercile 3			−0.088	−0.048			0.042	0.094	0.142**
			(0.041)**	(0.037)			(0.073)	(0.073)	
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	.02	.05	.06	.06	.02	.05	.06	.06	
N	1,103	1,103	1,103	1,103	1,198	1,198	1,198	1,198	

Notes: Standard errors in parentheses. *$p < .1$, **$p < .05$, ***$p < .01$. Coefficients for the province, marital status, household size, number of children, and asset variables are not shown.

$$E[w_s] - w_0 > c_s,$$

while a permanent wage offer will be accepted when

$$w_p - w_0 > x_t,$$

TABLE A4 Migrant selection with network interactions and community-level controls

	(1) Permanent	(2) Temporary	(2) – (1) Difference
Age 25–34	0.086***	−0.058	−0.143**
	(0.040)	(0.048)	
Age 35–44	0.077**	−0.083	−0.16***
	(0.032)	(0.051)	
Age 45–54	0.085**	−0.072	−0.157***
	(0.034)	(0.058)	
Age 55–60	0.136**	−0.089	−0.225***
	(0.065)	(0.059)	
Migrant networks, tercile 2	−0.046	−0.014	0.032
	(0.100)	(0.094)	
Migrant networks, tercile 3	−0.021	0.009	0.029
	(0.103)	(0.108)	
Complete primary education	−0.014	−0.043	−0.029
	(0.03)	(0.038)	
× Migrant networks, tercile 2	−0.002	0.043	0.045
	(0.051)	(0.066)	
× Migrant networks, tercile 3	−0.047	0.02	0.068
	(0.074)	(0.063)	
Complete secondary education	0.047	0.161***	0.114**
	(0.056)	(0.047)	
× Migrant networks, tercile 2	−0.103	−0.222***	−0.119
	(0.084)	(0.067)	
× Migrant networks, tercile 3	0.088	−0.120	−0.032
	(0.072)	(0.086)	
Higher than secondary education	0.131*	−0.031	−0.162**
	(0.074)	(0.051)	
× Migrant networks, tercile 2	−0.184*	−0.043	0.141
	(0.105)*	(0.069)	
× Migrant networks, tercile 3	−0.218**	0.054	0.272**
	(0.091)	(0.083)	
Digit span *z*-score	−0.004	0.026	0.03
	(0.052)	(0.033)	
× Migrant networks, tercile 2	0.029	0.054	0.025
	(0.073)	(0.045)	
× Migrant networks, tercile 3	0.141**	0.058	−0.083
	(0.059)	(0.040)	

(Continues)

TABLE A4 (Continued)

	(1) Permanent	(2) Temporary	(2) – (1) Difference
Dist. to primary road, tercile 2	−0.118	−0.103	0.015
	(0.105)	(0.191)	
× Migrant networks, tercile 2	0.044	0.081	0.037
	(0.150)	(0.190)	
× Migrant networks, tercile 3	0.166	0.091	−0.075
	(0.137)	(0.184)	
Dist. to primary road, tercile 3	−0.284***	−0.109	0.174
	(0.103)	(0.115)	
× Migrant networks, tercile 2	0.195	0.154	−0.042
	(0.161)	(0.144)	
× Migrant networks, tercile 3	0.280**	0.084	−0.195
	(0.124)	(0.128)	
Village has electricity (1988)	0.018	−0.045	−0.063
	(0.027)	(0.033)	
Village has public transport (1988)	−0.001	0.162**	0.164*
	(0.043)	(0.076)	
Unskilled male wages (Rs./day, 1986–7 average)	0.000	−0.002*	−0.002
	(0.000)	(0.001)	
Village population (1986)	0.000	0.000	0.000**
	(0.000)	(0.000)	
Percent of households owning land (1986)	−0.003	0.062	0.065
	(0.066)	(0.068)	
Percent of village population that is artisans (1991)	−1.690	−6.451*	−4.761
	(1.775)	(3.578)	
Percent of land uncultivated (1991)	−0.037	0.213*	0.250**
	(0.087)	(0.113)	
Constant	0.216*	0.460**	
	(0.108)	(0.184)	
R^2	.09	.10	
N	1,103	1,198	
F-test p-value: digit span–network variables = 0	.02	.32	
F-test p-value: education–network variables = 0	.15	.04	
F-test p-value: road–network variables = 0	.16	.88	

Notes: Standard errors in parentheses. *$p < .1$, **$p < .05$, ***$p < .01$. Specifications follow those estimated in Table 2; some coefficients are suppressed for the sake of brevity.

where

$$x_t = \begin{cases} \beta[\varphi(w_p,t+1) - \vartheta(w_p,t+1), & \text{for } w_p < y, \\ \beta[\varphi(w_p,t+1) - \vartheta(w_p,t+1)] + \beta \int_{w_p}^{\infty} [\varphi(w,t+1) - \varphi(w_p,t+1)] f(w) dw - c_p, & \text{for } w_p \geq y, \end{cases}$$

TABLE A5 Migrant selection with network interactions, inverse probability weights

	(1) Permanent	(2) Temporary	(2) - (1) Difference
Age 25–34	0.083**	−0.067	−0.151**
	(0.038)	(0.049)	
Age 35–44	0.072**	−0.091*	−0.163***
	(0.029)	(0.053)	
Age 45–54	0.083**	−0.079	−0.162**
	(0.032)	(0.059)	
Age 55–60	0.129**	−0.093	−0.223***
	(0.062)	(0.057)	
Migrant networks, tercile 2	−0.033	−0.050	−0.017
	(0.098)	(0.083)	
Migrant networks, tercile 3	−0.025	−0.009	0.017
	(0.096)	(0.105)	
Complete primary education	−0.012	−0.039	−0.028
	(0.028)	(0.038)	
× Migrant networks, tercile 2	−0.009	0.051	0.059
	(0.049)	(0.066)	
× Migrant networks, tercile 3	−0.047	0.028	0.075
	(0.069)	(0.070)	
Complete secondary education	0.045	0.171***	0.126**
	(0.052)	(0.049)	
× Migrant networks, tercile 2	−0.116	−0.209***	−0.093
	(0.077)	(0.066)	
× Migrant networks, tercile 3	−0.084	−0.133	−0.048
	(0.066)	(0.090)	
Higher than secondary education	0.129*	−0.003	−0.132**
	(0.072)	(0.057)	
× Migrant networks, tercile 2	−0.185*	−0.050	0.135
	(0.102)	(0.073)	
× Migrant networks, tercile 3	−0.214**	0.040	0.254**
	(0.087)	(0.093)	
Digit span *z*-score	−0.009	0.021	0.029
	(0.051)	(0.037)	
× Migrant networks, tercile 2	0.043	0.049	0.006
	(0.071)	(0.048)	
× Migrant networks, tercile 3	0.144**	0.075*	−0.069
	(0.058)	(0.044)	

(Continues)

TABLE A5 (Continued)

	(1) Permanent	(2) Temporary	(2) - (1) Difference
Dist. to primary road, tercile 2	−0.130	−0.055	0.074
	(0.105)	(0.211)	
× Migrant networks, tercile 2	0.086	0.050	−0.036
	(0.146)	(0.193)	
× Migrant networks, tercile 3	0.209	0.108	−0.100
	(0.130)	(0.209)	
Dist. to primary road, tercile 3	−0.268**	−0.075	0.193
	(0.100)	(0.119)	
× Migrant networks, tercile 2	0.179	0.233*	0.055
	(0.160)	(0.135)*	
× Migrant networks, tercile 3	0.273**	0.126	−0.146
	(0.115)	(0.132)	
Constant	0.213**	0.293**	
	(0.087)	(0.110)	
R^2	.09	.08	
N	1,103	1,198	
F-test p-value: digit span–network variables = 0	.02	.23	
F-test p-value: education–network variables = 0	.15	.08	
F-test p-value: road–network variables = 0	.08	.40	

Notes: Standard errors in parentheses. *$p < .1$, **$p < .05$, ***$p < .01$. Specifications follow those estimated in Table 2; some coefficients are suppressed for the sake of brevity.

and y represents the lowest wage draw for which search will continue. The wage y is determined by equating the value functions for (1) and (2):

$$c_p = \beta \int_y^\infty [\varphi(w,t+1) - \varphi(y,t+1)] f(w) dw.$$

The search for permanent migration opportunities will cease when the expected value of continued search no longer exceeds the cost, so the decision to engage in permanent migration depends on whether search remains ongoing. There are likely to be some individuals for whom 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).

Self-selection. Even with different dynamic considerations for temporary and permanent migration, differences in expected wages will drive the majority of migration decisions. To examine how the duration of migration episodes may affect patterns of self-selection, suppose wages and search costs are functions of individual characteristics, similar to Chiquiar and Hanson (2005):

$$\begin{aligned}
\ln w_0 &= \mu_0 + \delta_0(H), \\
\ln w_p &= \mu_p + \delta_p(H) + \epsilon_p, \quad \text{with } \epsilon_p \sim F_i(\cdot),\ c_p = \pi_p - \theta_p(H,W), \\
\ln w_s &= \mu_s + \delta_s(H) + \epsilon_{st}, \quad \text{with } \epsilon_{st} \sim G_t(\cdot),\ c_s = \pi_s - \theta_s(H,W).
\end{aligned}$$

TABLE A6 Probability of remaining in sample

	Dummy – in sample
Born during 1962–76	−0.06**
	(0.03)
Born during 1977–91	−0.08***
	(0.03)
1991 household assets, tercile 2	0.02
	(0.03)
1991 household assets, tercile 3	−0.09**
	(0.04)
1991 household size, tercile 2	0.00
	(0.02)
1991 household size, tercile 3	0.03
	(0.03)
Percentage of 1991 village members who 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

Notes: Marginal effects presented. Standard errors in parentheses. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. 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.

In each market, μ represents the mean wage, and δ is a skill price for human capital (H). Search costs are affected by human capital as well as other factors (W) such as wealth, migrant networks, household composition, and access to roads. We assume that search costs are decreasing in human capital for both permanent and temporary migration, but the returns to human capital need not be higher in migrant labor markets. One of the main findings that is produced by the model is that the likelihood of either temporary or permanent migration, conditional on having never previously migrated, depends on the current wage draw.

Our empirical analysis focuses only on the first observed migration episode, as we do not have comprehensive migration histories. Therefore, we take the same approach with our theoretical model rather than fully characterizing the solution to the dynamic problem. Then, in any period t, the likelihood of

TABLE A7 Migrant selection with network interactions (Logit)

	(1) Permanent	(2) Temporary	(2) – (1) Difference
Age 25–34	0.112**	−0.054	−0.182***
	(0.050)	(0.043)	
Age 35–44	0.104***	−0.077	−0.192***
	(0.038)	(0.047)	
Age 45–54	0.111***	−0.069	−0.194***
	(0.043)	(0.055)	
Age 55–60	0.159***	−0.079	−0.262***
	(0.059)	(0.055)	
Migrant networks, tercile 2	−0.004	−0.011	−0.004
	(0.116)	(0.089)	
Migrant networks, tercile 3	0.018	0.030	0.004
	(0.109)	(0.100)	
Complete primary education	−0.036	−0.047	0.004
	(0.081)	(0.067)	
× Migrant networks, tercile 2	0.022	0.052	0.018
	(0.090)	(0.085)	
× Migrant networks, tercile 3	−0.007	0.039	0.042
	(0.092)	(0.086)	
Complete secondary education	0.083	0.163***	0.040
	(0.086)	(0.038)	
× Migrant networks, tercile 2	−0.137	−0.200***	−0.005
	(0.110)	(0.060)	
× Migrant networks, tercile 3	−0.113	−0.138*	0.019
	(0.089)	(0.072)	
Higher than secondary education	0.153*	0.008	−0.179*
	(0.084)	(0.063)	
× Migrant networks, tercile 2	−0.198*	−0.060	0.189
	(0.105)	(0.076)	
× Migrant networks, tercile 3	−0.215**	0.010	0.270**
	(0.089)	(0.085)	
Digit span z-score	−0.009	0.029	0.035
	(0.059)	(0.039)	
× Migrant networks, tercile 2	0.030	0.035	−0.007
	(0.073)	(0.049)	
× Migrant networks, tercile 3	0.107*	0.046	−0.091
	(0.059)	(0.043)	

(Continues)

TABLE A7 (Continued)

	(1) Permanent	(2) Temporary	(2) – (1) Difference
Dist. to primary road, tercile 2	−0.074	−0.043	0.054
	(0.095)	(0.178)	
× Migrant networks, tercile 2	0.030	0.035	−0.007
	(0.073)	(0.049)	
× Migrant networks, tercile 3	0.107*	0.046	−0.091
	(0.059)	(0.043)	
Dist. to primary road, tercile 3	−0.248**	−0.039	0.268**
	(0.100)	(0.117)	
× Migrant networks, tercile 2	0.195	0.199	−0.066
	(0.155)	(0.127)	
× Migrant networks, tercile 3	0.248**	0.083	−0.230*
	(0.111)	(0.122)	
N	1,103	1,198	
F-test *p*-value: digit span–network variables = 0	.04	.56	
F-test *p*-value: education–network variables = 0	.10	.01	
F-test *p*-value: road–network variables = 0	.02	.45	

Notes: Standard errors in parentheses. *$p < .1$, **$p < .05$, ***$p < .01$. Specifications follow those estimated in Table 2; some coefficients are suppressed for the sake of brevity.

either temporary or permanent migration, conditional on having never previously migrated, depends only on the current wage draw:

$$\Pr[\epsilon_s > (\mu_0 - \mu_s) + (\delta_0 - \delta_s) + c_s], \quad \Pr[\epsilon_p > (\mu_0 - \mu_p) + (\delta_0 - \delta_p) + x_t],$$

with x_t defined as above. This formulation is purposely very general, as the limited research comparing permanent and temporary migration provides no clear guidance *a priori* for specifying explicit relationships between individual characteristics and the two different types of migration.

Human capital. Figure A1 shows how selection into migration is determined by wages net of search costs in the home ($\ln w_0$), temporary migrant ($\ln w_s - c_s$), and permanent migrant ($\ln w_p - c_p$) markets. We have depicted the case where the returns to human capital are highest for permanent migration, followed by the home market, with the lowest returns in temporary migration ($\delta_s < \delta_0 < \delta_p$). If base search costs (π) are sufficiently high ($\mu_0 > \mu_i - \pi_i$ for $i = s,p$) and the support for the human capital distribution runs from some value below H_L to some value above H_U, then we will have intermediate selection among temporary migrants and strictly positive selection among permanent migrants. If search costs are also substantially higher for permanent migration ($c_p > c_s$), as shown in Figure A1, then we additionally observe stronger positive selection for permanent migrants than for temporary migrants ($H_P > H_U$).

TABLE A8 Migrant selection with network interactions (multinomial logit)

	(1) Permanent	(2) Temporary	P-value, difference
Age 25-34	0.102**	−0.074*	0.00***
	(0.042)	(0.039)	
Age 35-44	0.096***	−0.096**	0.00***
	(0.035)	(0.042)	
Age 45-54	0.103***	−0.089*	0.00***
	(0.038)	(0.049)	
Age 55-60	0.142***	−0.112**	0.00***
	(0.051)	(0.049)	
Migrant networks, tercile 2	0.004	−0.008	0.94
	(0.093)	(0.075)	
Migrant networks, tercile 3	0.018	0.027	0.99
	(0.084)	(0.082)	
Complete primary education	–0.023	–0.034	0.98
	(0.071)	(0.062)	
× Migrant networks, tercile 2	0.011	0.039	0.90
	(0.078)	(0.079)	
× Migrant networks, tercile 3	–0.020	0.041	0.67
	(0.081)	(0.078)	
Complete secondary education	0.042	0.139***	0.60
	(0.071)	(0.031)	
× Migrant networks, tercile 2	−0.084	–0.163***	0.91
	(0.094)	(0.061)	
× Migrant networks, tercile 3	–0.074	–0.106*	0.90
	(0.074)	(0.063)	
Higher than secondary education	0.119*	–0.008	0.12
	(0.070)	(0.053)	
× Migrant networks, tercile 2	–0.153*	–0.036	0.20
	(0.084)	(0.064)	
× Migrant networks, tercile 3	–0.181**	0.039	0.03**
	(0.073)	(0.073)	
Digit span *z*-score	–0.001	0.020	0.79
	(0.044)	(0.031)	
× Migrant networks, tercile 2	0.010	0.035	0.87
	(0.054)	(0.041)	
× Migrant networks, tercile 3	0.078*	0.025	0.20
	(0.043)	(0.035)	

(Continues)

TABLE A8 (Continued)

	(1) Permanent	(2) Temporary	P-value, difference
Dist. to primary road, tercile 2	–0.063	−0.015	0.74
	(0.084)	(0.165)	
× Migrant networks, tercile 2	0.051	0.019	0.82
	(0.110)	(0.147)	
× Migrant networks, tercile 3	0.099	0.046	0.68
	(0.094)	(0.164)	
Dist. to primary road, tercile 3	–0.195***	0.013	0.02**
	(0.069)	(0.096)	
× Migrant networks, tercile 2	0.124	0.152	0.77
	(0.114)	(0.098)	
× Migrant networks, tercile 3	0.190**	0.023	0.06*
	(0.077)	(0.099)	
Log pseudolikelihood	–967.95		
	1,346		
χ^2 test *p*-value: digit span–network variables = 0	.001		
χ^2 test *p*-value: education–network variables = 0	.003		
χ^2 test *p*-value: road–network variables = 0	.000		

Notes: Standard errors in parentheses. *$p < .1$, **$p < .05$, ***$p < .01$. *p*-values in brackets for statistical difference in coefficient estimates across models. Specifications follow those estimated in Table 2; some coefficients are suppressed for the sake of brevity.