IN SEARCH OF A BETTER MATCH: QUALIFICATION MISMATCHES IN DEVELOPING ASIA

Kenn Chua and Natalie Chun

ASIAN DEVELOPMENT BANK

ADB Economics Working Paper Series

In Search of a Better Match: Qualification Mismatches in Developing Asia

Kenn Chua and Natalie Chun

No. 476 | February 2016

ASIAN DEVELOPMENT BANK

The ADB Economics Working Paper Series is a forum for stimulating discussion and eliciting feedback on ongoing and recently completed research and policy studies undertaken by the Asian Development Bank (ADB) staff, consultants, or resource persons. The series deals with key economic and development problems, particularly those facing the Asia and Pacific region; as well as conceptual, analytical, or methodological issues relating to project/program economic analysis, and statistical data and measurement. The series aims to enhance the knowledge on Asia's development and policy challenges; strengthen analytical rigor and quality of ADB's country partnership strategies, and its subregional and country operations; and improve the quality and availability of statistical data and development indicators for monitoring development effectiveness.

The ADB Economics Working Paper Series is a quick-disseminating, informal publication whose titles could subsequently be revised for publication as articles in professional journals or chapters in books. The series is maintained by the Economic Research and Regional Cooperation Department.

CONTENTS

TABLES AND FIGURES

TABLES

FIGURES

ABSTRACT

This paper empirically tests the role of search frictions in driving qualification mismatches in the labor market. Using new data from several low-income economies in urban Asia we find that overeducation in less developed labor markets are more pervasive than in more developed economies. Moreover, frictions related to search costs are a crucial determinant of match quality resulting in socially inefficient talent misallocation. Our findings suggest scope for policy interventions that improve worker-job matches with potential gains to wages and aggregate productivity.

I. INTRODUCTION

Mismatches between the skills that workers possess and what jobs require can have negative ramifications on productivity and social welfare (Acemoglu and Zilbotti 2001, Hsieh et al. 2013, Lise and Postel-Vinay 2015). For workers, mismatches can limit career progression and the skills that are developed on-the-job negatively impacting lifetime earnings (Baert, Cockx, and Verhaest 2013; Rogerson et al. 2005; Clark, Joubert, and Maurel 2014). Given the consequences of mismatches, identifying the factors affecting match quality is fundamentally important to determining the right types of policy interventions that can improve the matching process.

This paper examines the extent to which various factors explains talent misallocation in the form of qualification mismatches across six urban developing Asian economies using the World Bank's Skills towards Employability and Productivity (STEP) Skills Measurement Survey. In our model, match quality is defined based on a worker's perceptions about the level of education needed for the job in which he or she is employed compared to the education they possess. This potentially circumvents the issue of within-occupation job heterogeneity, which is not accounted for in alternative (e.g., statistical, normative) methods of determining qualification mismatches (e.g., Quinn and Rubb 2006).[1] Using a multinomial logistic model, we show that search frictions are a significant determinant of match quality even after inclusion of rich controls for human capital and local labor market conditions. Search frictions are found to operate through both the channel of informational asymmetries and credit constraints that impede poor households from investing significantly in the process of job search. This leads to poor households being far more likely to end up in jobs for which they are overqualified. While noncognitive and cognitive skills possessed by workers have been hypothesized to drive some of the observed mismatches, they appear to only play a relatively small role in the developing country context.

While observed mismatch could be driven by structural issues where equilibrium supply of skilled labor is insufficient to meet skilled labor demands, we find no evidence that this is the case. In fact, we find that similar to developed countries there are far larger shares of workers that have an education level that is greater than the jobs that are available. In developing Asia, this appears to be driven in part by weak labor market demand and could imply a greater role for policies that develop incentives for firms to employ higher skilled labor as opposed to greater investments and reforms to education (Lazear and Spletzer 2012, McGuinness 2006, Freeman 1976). While heterogeneous preferences could lead equally able and educated workers to choose occupations of dissimilar qualification (e.g., Gottschalk and Hansen 2003, Groh et al. 2015), or choose not to work at all, this seems less likely to be a factor in driving the disproportionately higher levels of overqualification mismatch among poorer populations.

To the best of our knowledge this is one of the first papers to empirically test a large set of factors influencing match quality in the context of developing countries. This is potentially an important omission from the literature as search frictions and lower reservation wages exacerbated by an absence of unemployment insurance among poor populations are hypothesized to be a significant determinant of the much larger informal sector that characterizes developing countries (Satchi and Temple 2009). Our empirical findings suggest that higher search costs and lower reservation wages likely arising from credit constraints among those with lower socioeconomic status drives this population set to enter less desirable informal sector jobs rather than to remain unemployed. While in developed countries the unemployed are more often both poor and less skilled, those who remain

---

[1] Mehta et al. (2011) find significant returns to education even in very narrow occupations this suggests that using a measure of overqualification mismatch based on mean or modal years in an occupation could significantly overestimate the level of overqualification in an economy.

unemployed in developing countries tend to be those that can afford to keep searching for a job that is better matched. This suggests an important role for policy to alleviate some of these distortions in job search and matching behavior that persist in developing countries due to search costs and socioeconomic status rather than innate skills (Card, Chetty, and Weber 2007).

Simple simulations suggest that reducing search costs and alleviating credit constraints could potentially improve the share of job-worker matches by as much as one-third. However, as better-off workers tend to have higher reservation wages, improvements could come at the cost of higher unemployment. In general, our findings are consistent with the literature that finds small subsidies for transport or to submit job applications can increase job-search intensity and ultimately facilitate greater job matches among poorer populations that face higher search costs (Bangladesh: Bryan, Chowdhury, and Mobarak 2014; US: Philips 2014; Ethiopia: Franklin 2015).

The economic consequences of search costs are potentially significant. Consistent with the existing literature, we find that those who are overqualified have higher wage returns compared to those in similar jobs that have the required level of education, but lower wages compared to similarly educated workers that are well matched (Allen and van der Velden 2001, Quinn and Rubb 2006). This contrasts with those that are underqualified having higher wage returns compared to workers with similar levels of education, but lower wage returns compared to those with required levels of education for which they are well matched (Leuven and Oosterbeek 2011). However, search frictions only weakly explain differences in returns to over and underqualification. This implies that improving search frictions would improve allocation of labor, but is unlikely to affect average levels of employment or wages except through the matching process. Ultimately, total gains to improved labor allocation will be bounded by the demand for skills in the labor market. Nevertheless, reducing search frictions, that are prominent among poorer populations and have long-term detrimental consequences on lifetime economic returns, could have a significant role in contributing to greater socioeconomic mobility and poverty reduction in developing countries.

The rest of this paper is organized as follows. In section II, we describe our data and its relevant features, as well as analyze patterns in the incidence of mismatch in our sample. In section III, we provide empirical evidence that barriers to search affect the likelihood of worker-job mismatch. In section IV, we examine the link between wages, search, and mismatch. Finally, section V concludes with some prospects for interpretation, policy, and future work.

II.   DATA

A.   The Skills towards Employability and Productivity Skills Measurement Surveys

The STEP Skills Measurement Program by the World Bank developed survey instruments tailored to collect data on skills in low- and middle-income country contexts. (Pierre et al. 2014) This includes information on educational attainment, job characteristics, and socioeconomic background. The samples per country comprise approximately 3,000 adults between the age of 15 and 64.

We focus on a subset of countries for which there is data available: Armenia, the People's Republic of China (PRC) (Yunnan), Georgia, the Lao People's Democratic Republic (Lao PDR), Sri Lanka, and Viet Nam. The years of data collection are 2012 for the PRC (Yunnan), the Lao PDR, Sri Lanka, and Viet Nam; and 2013 for Armenia and Georgia. The target population of the surveys varies from one country to another. Armenia and Georgia samples only individuals in urban areas of the

country excluding regions experiencing conflict. On the other hand, the Lao PDR and Sri Lanka target both urban and rural areas of the country. The sample from Viet Nam is collected from urban areas in Ha Noi and Ho Chi Minh City. Meanwhile, the target population for the PRC (Yunnan) is limited to the urban areas of Kunming, the largest city in the province of Yunnan. We restrict our analyses to the urban, nonmilitary active labor force residing in these areas due to distinct differences in labor markets between urban and rural sectors and as a rural subsample is not available for many of the country datasets. As the countries are analyzed under a single framework, we apply population weights representing the urban areas covered by the surveys, and wage rates are converted into dollars using purchasing power parities (PPPs).

Similar to the Organisation for Economic Co-operation and Development (OECD) Survey of Adult Skills (PIAAC), the STEP survey offers a unique opportunity to study the stock and use of human capital in less developed economies where data of this kind tend to be a rarity. Apart from information on years of education, employment, and demographic characteristics, we also utilize measures of cognitive reading ability, socioemotional skills, and information on tasks on the job. Of specific relevance to our study is a question on the worker's assessment of the educational attainment required for his job.

The countries covered by the data comprise a diverse set of developing Asian economies. Both the PRC (Yunnan) and Viet Nam are economies that have rapidly modernized over the past few decades evolving from centrally planned to market economies. While they have started from a relatively low base of education and skills, they have been steadily increasing their investments to meet their ambitions of moving up the global value chain. In contrast, Armenia and Georgia have been struggling to modernize and transition to a market economy despite having some of the highest levels of tertiary educated workers in the region. In contrast to the PRC and Viet Nam, their labor markets are characterized by much higher levels of unemployment and greater levels of formalization. In contrast, both Sri Lanka and the Lao PDR are the poorest of the six economies and remain largely agrarian. These economies have been struggling to industrialize and have far fewer tertiary educated workers. We find that these features of the labor market and macroeconomy interact with supply to determine equilibrium match outcomes.

B.   Summary Statistics

A summary of key variables describing our sample is presented in Table 1. The combined sample size of 7,720 comprises individuals who are active in the labor force and with different educational and professional attainment.

To measure years of education acquired, we use the theoretical years possessed by a worker who has finished a given level of formal schooling. Meanwhile, to identify required schooling, we use the respondent's answer to the question, "What do you think is the minimum level of formal education that would be required before someone would be able to carry out this work?" To map levels to years of education, we follow the United Nations Educational, Scientific and Cultural Organization (UNESCO) International Standard Classification of Education (ISCED) 1997 crosswalk.

Table 1: Summary Statistics–Sample of Active in the Labor Force in Urban Areas (15–64 years old)

	Pooled	Armenia	PRC (Yunnan)	Georgia	Lao PDR	Sri Lanka	Viet Nam
Years of education acquired	11.84	13.13	12.68	14.99	9.53	10.90	11.33
	(4.16)	(2.70)	(3.52)	(2.80)	(5.17)	(3.38)	(4.41)
Years of education needed[a]	10.42	12.72	11.69	14.09	8.19	10.58	9.58
	(4.79)	(4.43)	(3.46)	(3.62)	(5.57)	(3.63)	(5.17)
% Mismatch incidence using difference bet. years of education required and possessed:							
Well matched	37.0	23.3	46.4	25.6	33.2	43.7	35.6
Overqualified	38.6	21.5	37.9	22.9	42.9	28.2	46.4
Underqualified	14.6	17.2	10.9	5.2	22.1	21.8	14.4
Unemployed	9.7	38.0	4.8	46.3	1.9	6.3	3.6
Mean age	38.95	39.02	39.40	38.85	36.46	38.61	39.17
% Female in population	53.35	63.05	46.79	62.08	56.61	39.13	56.85
% Socioeconomic status at age 15:							
Low income	26.40	8.43	28.19	8.04	30.31	22.03	31.99
Middle income	60.14	49.12	60.92	51.45	61.36	66.24	60.99
High income	13.46	42.44	10.89	40.50	8.33	11.74	7.02
% Share reporting search difficulty due to:							
Lack of access to information on vacancies	23.77	18.13	30.05	16.13	50.33	16.63	21.67
Difficulty in application-related processes	27.90	13.35	39.39	25.36	38.66	19.02	26.57
Difficulty certifying one's ability	35.47	13.34	44.67	20.33	53.46	24.45	37.97
Lack of work experience	25.13	21.20	24.20	24.21	42.14	12.63	27.54
% Share of employment by sector:[a]							
Formal wageworker	41.76	81.19	51.41	38.99	17.95	37.52	38.33
Informal wageworker	25.17	8.68	33.34	48.11	26.53	24.34	21.22
Self-employed	33.08	10.13	15.25	12.90	55.51	38.14	40.45
% Share of employment by occupation:[a]							
High-skill white collar	30.12	51.91	26.55	54.29	23.82	34.06	27.54
Low-skill white collar	38.72	26.23	46.84	24.40	32.18	25.98	69.07
Crafts and related trade worker	19.02	13.64	13.46	12.22	13.12	26.50	21.25
Elementary and skilled agricultural worker	12.14	8.21	13.13	9.09	30.89	13.46	9.68
Log (*ln*) hourly wage in PPP[a]	0.90	0.98	0.96	1.08	0.36	0.98	0.91
	(0.98)	(0.76)	(0.74)	(0.84)	(1.24)	(1.02)	(1.04)
Observations (*n*)	7,720	1,392	1,259	1,383	973	563	2,142

Lao PDR = Lao People's Democratic Republic, PPP = purchasing power parity, PRC = People's Republic of China, STEP = Skills towards Employability and Productivity.
[a] Derived from subsample of employed individuals.
Notes: Weighted sample shares are as follows: Armenia 6.96, the PRC (Yunnan) 20.19, Georgia 7.52, the Lao PDR 5.98, Sri Lanka 12.88, and Viet Nam 46.47. Share of jobs by education required uses supplied assessment by workers. Standard deviation in parentheses. Occupation categories are based on reduced groups of the International Standard Classification of Occupations 2008. Managers, professionals, and associate professionals make up the high-skilled or high-skill white collar occupations. Low-skill white collar occupations include clerical support workers and service and sales workers. Crafts and related trade workers also include plant operators and assemblers. Finally, agricultural workers and elementary occupations make up the last group.
Source: Authors' estimates based on World Bank STEP surveys.

The use of direct assessment presents a clear methodological advantage and novelty in measuring the education needed by occupations in developing economies.[2] We find that for all countries, the schooling acquired by the working population in the aggregate always exceeds years needed.

Figure 1 depicts this comparison between the skill distribution in every country and worker–assessed skill demands. The former is based on the sample of employed and unemployed, while the latter is based on information provided by employed individuals about their jobs. For illustrative purposes, education in this figure is grouped into primary or less (ISCED 1 or less), lower secondary (ISCED 2), upper secondary (ISCED 3 and 4), and tertiary (ISCED 5 or higher). On the supply side, we find that Central Asian countries Armenia and Georgia feature a well-educated labor force with above 60% of the active workforce possessing tertiary qualifications. This level of education attainment is comparable with those in advanced economies. Meanwhile in the PRC (Yunnan), Sri Lanka, and Viet Nam, more than 80% of workers have completed at least lower secondary school. In contrast in the Lao PDR, more than a third of the labor force possesses only primary school qualifications or less.

Figure 1: Distribution of Education Acquired and Required by ISCED Levels

ARM = Armenia, GEO = Georgia, ISCED = International Standard Classification of Education, LAO = Lao People's Democratic Republic, PRC = People's Republic of China, SRI = Sri Lanka, VIE = Viet Nam.
Note: Shares of required schooling total to 1 minus unemployment rate.
Sources: Skills towards Employability and Productivity (STEP); authors' computations.

---

[2]   Previous studies have often relied on mean or modal completed schooling levels of workers in the same occupation as a measure of required schooling. As Leuven and Oosterbeek (2011) reason, use of this approach is often regarded as inferior as realized matches are the result of demand and supply forces. This approach will tend to overstate (understate) required education where overqualification (underqualification) is pervasive. Mismeasurement is also likely to worsen with smaller sample sizes and larger variance of job requirements within occupations as is likely the case in segmented labor markets in low-income nations.

In Table 1, we also report the incidence of mismatch for the pooled sample and across countries. We define overeducation (undereducation) as having completed years of schooling above (below) what is needed for the job. Among the six, urban Viet Nam has the highest share of individuals working in jobs for which they are overqualified. Underqualification is most prevalent in Armenia, where 29.1% lack years of schooling that meet job requirements. On the other hand, we find that overqualification is more acute in less developed Asian labor markets relative to its incidence in the United States (US), where the rate of overqualification measured using worker assessment stands at 29%.[3] The incidence of underqualification is lower for our sample of countries, at 11.6%, compared with the 16% reported in the US.

The prevalence of overqualification in developing Asia does not necessarily convey that the stock of skills is adequate to address current requirements much less those of the future. Indeed the problem of mismatch is concerned with the balance of supply and demand as well as the efficiency of the labor market matching the two (Shimer and Smith 2000, Shimer 2005, Shimer 2007). Moreover, there are substantial heterogeneities in jobs and skills that underlie this. In developing Asia, we find that employment belongs primarily to informal wage work or self-employed sectors with the exception of Armenia. Consistent with a segmented or dual labor market theory, studies have found that employment in these sectors largely comprise jobs with low wages and skill requirements (e.g., Fields 1975, Gunther and Launov 2012). In terms of occupations, relatively high-skilled countries like Armenia and Georgia have greater proportions of high-skilled white collar occupations. In other countries, the bulk of workers are in low-skill white collar occupations, crafts and related trade, and agricultural or elementary occupations.[4]

Realized matches between job and worker in the cross-section may also reflect search inefficiencies that give rise to inefficient investments in education or a misallocation of existing labor. For instance, the prevalence of asymmetric information, such as from difficulty demonstrating one's abilities, may cause workers to invest in greater amounts of education to signal their quality even while further schooling may provide little value in enhancing their productivity for the jobs available thus leading to a prevalence of overqualified workers (Spence, 1973). Alternatively, workers may encounter difficulties finding jobs for which their set of skills is appropriate because of limited networks or lack of knowledge even while they have the right skills and qualifications.

To proxy for these search frictions, we use survey instruments that ask the respondent, "If you were in the position that you were looking for work, do you think you have the means to find out about job vacancies?" A similar question is also asked regarding the respondent's ability to prepare a resume, fill out job applications, and perform job interviews, as well as the respondent's means to certify or demonstrate qualifications. We construct three variables that correspond to a negative response to these queries: an indicator for difficulty in finding vacancies, an indicator for difficulty navigating the job application process, and an indicator for difficulty certifying one's credentials. The share of workers in our sample reporting such problems are 24%, 28%, and 35% respectively.

---

[3] The incidence of overqualification (underqualification) is also higher (lower) in our sample of Asian countries than the OECD, which is at 21% (11.6%) according to a comparison of education levels attained and required (OECD 2013).

[4] These occupation classifications are reduced categories of ISCO-08 codes. Managers, professionals, and associate professionals make up the high-skilled or high-skill white collar occupations. Low-skill white collar occupations comprise clerical support workers and service and sales workers. Crafts and related trade workers also include plant operators and assemblers. Finally, agricultural workers and elementary occupations make up the final group.

C.   Patterns of Mismatch in Developing Asia

In Table 2, we compare the distribution of mismatch across demographic, sectoral, and occupational lines. We find that women are 4 percentage points more likely to be overqualified, while men are slightly more likely to be matched or underqualified. Moreover, we find that overqualification tends to be more common among midcareer workers, which contrasts with developed countries where the incidence of reported overqualification is more prominent among younger workers. Many young workers may enter jobs for which they are overqualified and where present returns are lower if it allows them to gain important skills resulting in higher probabilities of promotion later (Sicherman and Galor 1990, Altonji and Pierret 2001). In contrast, underqualification is more prevalent among workers approaching retirement, which could be consistent with rising education levels and changing job expectations in developing countries. However, there is evidence that younger workers disproportionately face greater challenges in finding a job match as they have disproportionately higher levels of unemployment. This could arise from greater difficulties in signaling their ability, lack of information or experience with job search. Unrealistic expectations about the type of jobs that they can obtain given their education, skills, and experience could also play a role.

Table 2: Distribution of Education Mismatch by Sector, Pooled Sample of Active in Labor Force

	Education–Job Match			
	Well Matched	Overqualified	Underqualified	Unemployed
Female	35.44	40.39	13.34	10.83
Male	38.89	36.63	16.05	8.43
Early career (15–25 years old)	34.04	31.92	11.26	22.77
Midcareer (26–54 years old)	38.06	40.17	14.39	7.38
Late career (55–64 years old)	34.16	37.15	20.63	8.06
Primary or less (<=ISCED 1)	31.82	33.44	32.01	2.73
Lower secondary (ISCED 2)	38.37	38.36	17.59	5.68
Upper secondary (ISCED 3–4)	40.26	33.79	13.61	12.34
Postsecondary (>=ISCED 5)	35.05	46.31	6.06	12.58
Low SES at age 15	35.73	42.71	16.25	4.81
Middle SES at age 15	37.71	38.85	14.42	9.01
High SES at age 15	36.76	29.52	11.29	22.42
Formal wageworker	46.79	37.35	15.86	
Informal wageworker	41.51	42.04	16.45	
Self-employed	33.41	50.23	16.36	

ISCED = International Standard Classification for Education, SES = socioeconomic status, STEP = Skills towards Employability and Productivity.
Source: Authors' estimates based on World Bank STEP surveys.

We also find that those from economically disadvantaged backgrounds that had low and middle socioeconomic status at age 15 are much more prone to being overqualified. This gives strong credence to the claim that credit and informational constraints could potentially be impeding job search especially in developing country economies where unemployment insurance is absent. This potentially is reflected in the finding that those that are economically disadvantaged are far less likely to be unemployed. This particular feature of developing country economies could result in less than optimal match outcomes in the labor market especially as those that are more credit constrained may be less likely to continue to search for a better job due to perceived costs of undertaking job search and the need to more immediately generate a source of income (Card, Chetty, and Weber 2007).

Comparing across skill levels, we observe that those with an upper secondary degree are more likely to find jobs for which their qualifications are well suited. Meanwhile, those finishing with a tertiary

degree are more likely to report being overqualified suggesting they are performing tasks in their jobs that do not require a tertiary education.

As emphasized, labor markets in developing countries are unique for their large shares of informal sector employment. This sector is comprised largely by either microenterprises or menial wage work, which often do not require high levels of skill or training. We find that the more competitive formal wage sector better matches workers to jobs than the informal salaried and self-employed sectors. In fact, overeducation is particularly severe among self-employed workers. This is plausibly explained by the preponderance of small businesses with low skill requirements.[5]

D.   Measured Ability: Cognitive Reading Skills, Noncognitive Skills, and Reported Skill Deficiencies

Our dataset contains detailed information on the stock of human capital possessed by the worker. Aside from years of education and experience as proxied by age, STEP also includes measures of hard and soft skills, as well as self-reported skill deficits in experience, reading skills, and computer knowhow. To measure cognitive reading ability, STEP conducts an assessment through a review of three cognitive reading operations: access and identify, integrate and interpret, evaluate and reflect. Cognitive skills have been defined as the ability to understand complex ideas, adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, and to overcome obstacles through problem solving (Neisser et al. 1996). The test contains four sections: vocabulary, sentence processing, passage comprehension as well as a core literacy assessment. The last of which is used to screen respondents for eligibility to take a second, more difficult battery of exercises. Because not all countries are able to conduct this second round of literacy assessment, we construct our measure of cognitive literacy skills around the four components mentioned above using information on the number of correct answers. This comes at the expense of having smaller variations in measured skills as many individuals perform well in these components. To compute our cognitive reading ability score, we divide the number of correct answers by the number of items in each component. A simple average of these computed scores yields one's cognitive literacy score.

Socioemotional or character skills are measured through eight emotional, personality, and attitudinal traits, each scaled from 1–4 with 4 being the highest or most desirable. These include conscientiousness, openness to experience, stability, agreeableness, extraversion, hostile attribution bias (reversed), grit, and decision making.[6] Because these traits correlate differently with various labor market outcomes across countries (e.g., grit is more correlated with wages in Viet Nam, while openness to experience is more correlated with wages in the PRC) and our purpose is to measure overall levels of noncognitive skills rather than identify the effect of each individual trait, we construct a simple measure of noncognitive ability by summing the eight variables and dividing this sum by the highest possible score of 32. Both cognitive and noncognitive skill measures are then normalized to have zero

---

[5]   While the self-employed may be able to choose more challenging occupations that have higher returns, capital constraints, lack of entrepreneurial skills, and market demand may prevent these individuals from pursuing these types of occupations.

[6]   Conscientiousness has been defined as the propensity to be goal directed and follow norms and rules. Openness to experience refers to enjoyment of learning. Stability relates with one's disinclination to feel negative emotions. Agreeableness refers to prosocial orientation with peers, while extraversion relates with sociability. These five comprise the Big Five taxonomy or domains of human personality. Moreover, grit relates with perseverance for long-term goals. Hostile attribution bias has been defined as the tendency to interpret others' behaviors or actions as hostile. Finally, decision making relates with due diligence taken prior to reaching a decision. The addition of the latter three to the Big Five provides incremental predictive power over measures of professional and educational achievement (Pierre et al. 2014).

mean and unit standard deviation within countries. We find the choice of within and cross-country standardization does not materially change our results.

Finally, we also utilize information on reported deficiencies in literacy, computer skills, and work experience. The first two are dummies from responding affirmatively to the question, "Has a lack of reading and writing skills (computer skills) ever kept you from getting a job, a promotion, or a pay rise, or held you back from advancing your business or you own account activity?" The latter refers to a dummy for an affirmative response to a question asking whether lack of experience would be an impediment if the person had been searching for a job today.

III.   THE ROLE OF SEARCH: EMPIRICAL EVIDENCE

A.   Empirical Strategy

High search costs and credit constraints can play an important role in driving worker-job mismatch. Worker search costs can generate substantial talent misallocation resulting in workers' not realizing their first best job prospects or alternatively not obtaining a job at all (Pissarides 1979, Pissarides 1984). In this section, we examine whether this holds true empirically.

To do this, we model the likelihood of over and underqualification using a multinomial logistic (MNL) model. Previous studies predominantly use probit or similar binary outcome models to identify the determinants of worker-job match, either by cutting out the subsample of workers not being modeled (e.g., perform a probit to estimate odds of overqualification relative to appropriate matching by excluding underqualified individuals from the sample) (Quintini 2011) or by treating the nature of mismatch as the same (e.g., perform a probit to estimate odds of being mismatched versus appropriately matched) (Robst 2007, Green and McIntosh 2007). Chevalier (2003) and Chevalier and Lindley (2009) form a small minority that has utilized polychotomous outcome models.[7]

Our empirical model estimates the likelihood of an individual landing a job of match type k conditional on an individual's endowments and local labor market conditions. This is expressed by the model:

$$\Pr(Match_i = k) = \Lambda(S_i'\alpha_k + X_i'\beta_k + Z_j'\gamma_k + \delta_c)\left[1 + \sum_{k=2}^{4} \Lambda(S_i'\alpha_k + X_i'\beta_k + Z_j'\gamma_k + \delta_c)\right]^{-1}$$

where k = 1, 2, 3, 4 are match outcomes corresponding with well matched, underqualification, overqualification, and unemployed, respectively. The model originates from a random utility framework in which individual i optimally chooses alternative k. The systematic component of utility is comprised of the relevant search variables S_i, human capital and socioeconomic characteristics of the worker X_i, features of the local labor market j denoted by Z_j, and a set of country dummies δ_c. We assume that the unobserved component of the utility follows a Type-I extreme value distribution. To identify the alternative-specific parameters α_k, β_k, and γ_k, we set the parameters of the reference

---

[7]   Robst (2007) estimates determinants of the relatedness of field of training to job rather than level of education. Chevalier (2003) and Chevalier and Lindley (2009) estimate the probability of being genuinely and apparently overeducated versus being in a graduate job.

category k = 1 to 0. In effect, we are able to estimate the relative odds of being overqualified, underqualified or unemployed to being appropriately matched.

The choice of MNL over binary outcome models may be informationally more efficient and does not assume that the underlying causes of unemployment, underqualification and overqualification are the same. Thus the sign and magnitude of our parameter of interest, α_k, may differ depending on match outcome k. We hypothesize that higher search costs increase the odds of overqualification and decrease the likelihood of underqualification.

In addition, we also expect a statistically significant relationship between the match outcome and socioeconomic status at age 15, which captures a mixture of both credit constraints and higher search costs. Socioeconomic background could relate to the ease at which one obtains a job due to family or social connections or geographic location. While socioeconomic background could also be capturing the quality of education, our ability to control for an individual's current skills provides us with greater confidence that the variables contained in our model are more likely capturing factors related to search and informational costs and credit constraints. Those from more disadvantaged backgrounds tend to have higher search costs as they tend to be geographically further away from the primary labor markets and face greater informational constraints due to lack of connections (Calvo-Armengol and Jackson 2007). Individuals from better economic backgrounds should find it easier to find a job for which they are well matched as they are more easily able to smooth their consumption and delay entering a job that they find is a suboptimal match. Based on descriptive statistics, we find that those from economically poorer families and that have less educated parents are disproportionately more prone to report difficulties finding employment and are much more likely to be informally employed. Thus, we include marital status, presence of children, the numbers of older and younger siblings, parents' education, and dummies for the worker's economic status at age 15 in the MNL.

The MNL still poses nontrivial challenges in identifying causal estimates of our main variables of interest. Not only are we unable to address specification error using instrumental variables, but it is also more difficult to identify the direction of the bias (Lee 1982). [8] A large part of the reason is that we are unable to observe and control for many of the firm characteristics that drive the match to arise in the first place. This is a potentially important source of omitted variable bias, which would be addressed only in an experimental setting that randomly assigns workers of similar qualifications to particular types of jobs. To alleviate some of these concerns, we test several specifications and the sensitivity of our results to controls for likely sources of bias by including a battery of job characteristics.

Our rich controls for both cognitive and noncognitive skills allow us to address possible issues of endogeneity arising from unobserved differences in human capital. Ability differences may lead workers to jobs for which they are overqualified (underqualified) if surplus (deficit) schooling compensates for (is compensated by) deficiencies (excesses) in their human capital bundle. For instance, firms may require additional years of education to substitute for lack of experience or language proficiency. To limit bias arising from unobserved skill heterogeneity, we include a host of variables that proxy for human capital characteristics such as years of education completed, age, tenure, and measures of cognitive reading ability. We additionally control for overall levels of noncognitive ability. This is crucial as noncognitive skills have been found to strongly influence

---

[8] Under certain assumptions, Lee (1982) shows that a necessary and sufficient condition for the coefficient of the included explanatory variable to be unbiased is that the omitted and included explanatory variables are independent, conditional on the outcome or response variable.

behavior and labor market outcomes, notably educational attainment and wages (Heckman, Stixrud, and Urzua 2006). In addition, we include indicators for self-reported deficiencies in literacy and computer skills. We also directly measure the role of experience by supplying a self-reported indicator of the worker not having the necessary work experience if looking for a job.

A growing body of evidence in the field of urban economics has alluded to matching as one of the main sources of agglomeration economies in cities (Duranton and Puga 2004). Dense labor markets improve quality of the match through better diffusion of information and through hosting a greater variety of workers and opportunities (Berliant, Reed, and Wang 2006). Our estimates could be biased if correlations between urban density, individual search costs, and type of match are ignored. Recent research also indicates that it is equally important to account for local composition effects that reflect features of the local economy (Combes, Duranton, and Gobillon 2008). In keeping with this literature, we use population density to capture differences in agglomeration across regional labor markets.[9] To control for regional composition effects, we include industry shares based on four major categories, occupational shares on the four major International Standard Classification of Occupations (ISCO) categories, the share of the informal sector, the local incidence of mismatch, local unemployment rate, and the relative proportions of individuals in the region by skill level.[10] These are obtained from within the sample.

A final threat to the internal validity of our results is unobserved differences across cohorts as job-finding difficulty and likelihood of matching may systematically vary across age cohorts. One possibility is that cohorts face different market conditions upon entering the labor market. Tougher economic periods or technological progress over time may influence both search behavior and odds of matching by raising requirements for hiring success. To control for this, cohort-within-country fixed effects are constructed, spanning individuals in the same 5-year age group in the same country.

We begin the analysis by estimating the likelihood solely on the premise of a human capital story. These are compared to the baseline model with proxies for search costs. Thereafter, these findings are tested to examine their sensitivity to possible specification error in the model. For all estimates, robust standard errors clustered by urban labor market are reported.

B.   Results

Table 3 tabulates our estimates from a multinomial logistic regression using our pooled sample. For ease of interpretation, coefficients are expressed in terms of relative risk ratios so that a value greater than one implies higher odds of obtaining a job for which one is over or underqualified, or being unemployed, relative to being well matched, and a value less than one denotes lower associated odds of unemployment or over or underqualification relative to being well matched.

In column 1, we estimate a model of worker-job match with country fixed effects and a full set of human capital variables. Consistent with a human capital compensation hypothesis (Korpi and Tahlin 2009), a deficit in noncognitive skills is found to raise the relative risk of overqualification. Meanwhile, the converse scenario is found for the odds of underqualification and unemployment where strikingly only higher noncognitive skills possibly substitutes for lack of schooling.

---

[9]   Population density for each of the 51 regions was obtained from national statistical agencies for the year closest to the date of the survey.

[10]   The four major industrial classifications are agriculture, industry, commerce, and other services. The four major occupation categories are those categories noted in footnote 4.

In this paper, self-reported lack of experience on top of the standard age and squared age proxies for work experience are used. Estimates show that this is highly correlated with the type of match realized in the labor market with the relative risks of overqualification and unemployment rising by a factor of 1.9 and 3.2, or a near doubling and tripling, respectively, and the relative risk of underqualification falling by a factor of 0.6 under our baseline specification.

Testing the hypothesis that search costs also determine match quality, we include proxies for search difficulty in the model. Column 2 presents estimates from a model with the search variables. We begin by examining the relative odds of overqualification. Looking at proxies for search frictions, we find that difficulty certifying one's credentials presents a substantial constraint to appropriate worker-job match; relative risk of overqualification rises by a factor of 1.2. Meanwhile barriers to accessing information on vacancy and difficulty navigating the job application process are not found to be a significant predictor of the likelihood of mismatch, but have signs in the expected direction.

On the other hand, we find that underqualification is negatively related with search difficulties. Being adept at navigating the application process and being able to certify one's skills is associated with higher odds of underqualification. In contrast with earlier results, none of the search variables or socioeconomic variables are significantly correlated with the relative risk of being unemployed. This is likely a unique characteristic of the developing country context where higher search costs could drive people into different quality of job matches as opposed to determining differences in unemployment.

In columns 3, 4, and 5, we test whether results are biased by selection on unobservables. First, we find that the inclusion of demographic controls only marginally reduce the magnitude of the relative risk ratios of our variables of interest, with no change in overall significance. We also find that socioeconomic status during one's youth and parents' education are an important determinant of match type with those from higher-income families and highly educated parents realizing smaller odds of overqualification and unemployment and greater odds of being underqualified. Accounting for regional variation across labor markets does not affect the significance of these results. Finally our results are also robust to the inclusion of cohort fixed effects.

In simulations, where we examined eliminating search frictions and eliminating potential credit and informational constraints associated with socioeconomic status, we found that potential increases in the match probability could improve by as much as one-third (Figure 2). Our simulations suggest that unemployment potentially rises, consistent with improved allocation of job-worker matches resulting in larger shares of workers with higher reservation wages who may be less willing to work in the less productive informal sector. The improved job matches is potentially economically significant given the share of mismatches occurring in developing country labor markets and provides support for policies that potentially alleviate some of the search frictions that arise due to explicit search difficulties and higher search costs that are faced by lower socioeconomic groups. Nevertheless, it may come at the consequence of higher overall unemployment.

Overall, these findings support the theory that in a developing country labor market with search frictions, utility-optimizing agents may fail to achieve first best employment outcomes. From a policy perspective, this implies scope for improving the allocation of workers to jobs with potential gains not just in wages but also aggregate productivity. As workers from lower SES are disproportionately more likely to be less well matched, improving search frictions could also prove fruitful in improving labor market outcomes among the poor.

Table 3: Relative Risk Ratio of Education–Job Mismatch, Pooled Sample

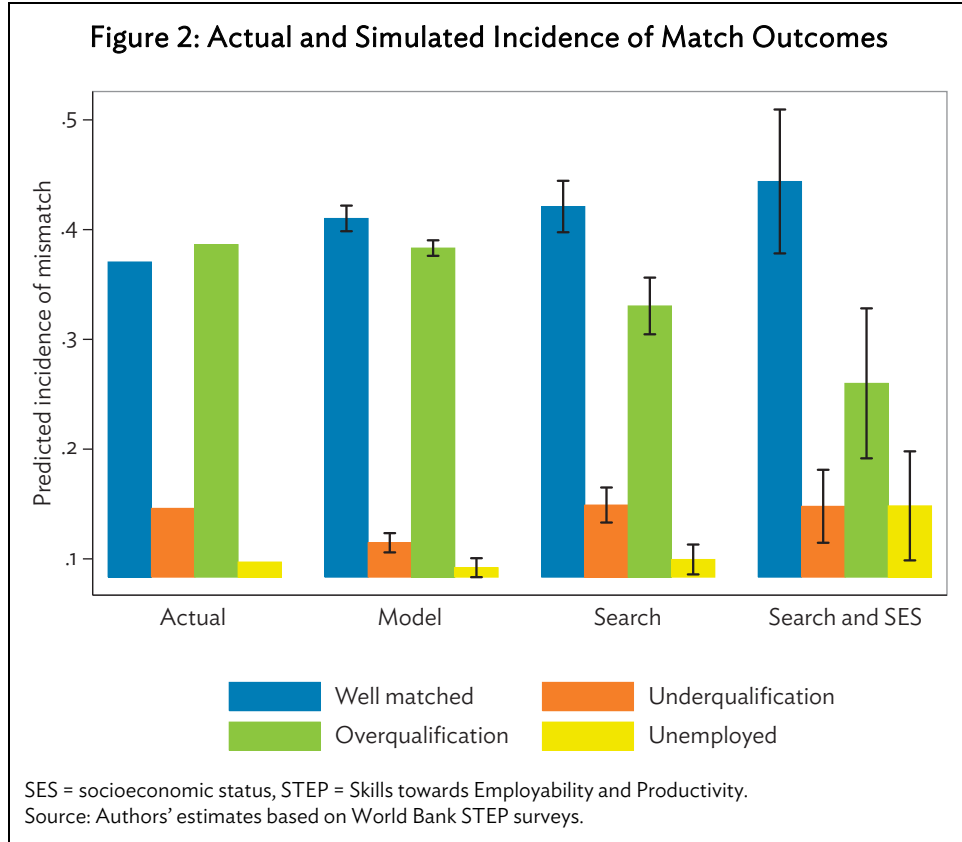|	(1)		(2)		(3)		(4)		(5)	
Undereducated										
Years of education	0.834***	[0.0436]	0.808***	[0.0418]	0.802***	[0.0397]	0.797***	[0.0402]	0.792***	[0.0403]
Sex (1 = Female)	0.943	[0.0973]	0.958	[0.0949]	1.000	[0.138]	0.993	[0.129]	0.992	[0.124]
Age	1.009	[0.0397]	1.012	[0.0397]	0.996	[0.0391]	0.996	[0.0389]	1.064	[0.0778]
Lack of experience	0.573***	[0.0520]	0.730***	[0.0461]	0.733***	[0.0338]	0.730***	[0.0426]	0.719***	[0.0453]
Literacy ability	1.049	[0.0518]	1.022	[0.0511]	1.002	[0.0504]	1.010	[0.0460]	1.013	[0.0449]
Noncognitive ability	1.184***	[0.0587]	1.144***	[0.0571]	1.103*	[0.0610]	1.108*	[0.0639]	1.109**	[0.0555]
Difficulty finding vacancy			0.834	[0.102]	0.868	[0.100]	0.892	[0.123]	0.893	[0.126]
Difficulty in app process			0.742***	[0.0702]	0.719***	[0.0589]	0.732***	[0.0763]	0.721***	[0.0714]
Difficulty certifying skills			0.689**	[0.123]	0.683*	[0.138]	0.665*	[0.161]	0.662*	[0.162]
Middle SES at age 15					1.073	[0.0872]	1.091	[0.0745]	1.104	[0.0680]
High SES at age 15					0.891	[0.135]	0.879	[0.133]	0.898	[0.146]
Overeducated										
Years of education	1.126***	[0.0209]	1.149***	[0.0139]	1.164***	[0.0189]	1.165***	[0.0201]	1.168***	[0.0208]
Sex (1 = Female)	1.094	[0.0616]	1.087*	[0.0514]	1.117**	[0.0496]	1.114**	[0.0493]	1.116**	[0.0497]
Age	1.008	[0.0268]	1.003	[0.0288]	0.988	[0.0231]	0.985	[0.0196]	0.973	[0.0247]
Lack of experience	1.933***	[0.0761]	1.563***	[0.108]	1.528***	[0.117]	1.520***	[0.114]	1.531***	[0.127]
Literacy ability	0.983	[0.0320]	0.993	[0.0337]	1.005	[0.0336]	1.006	[0.0342]	1.004	[0.0312]
Noncognitive ability	0.921***	[0.0240]	0.942*	[0.0328]	0.927***	[0.0203]	0.933***	[0.0220]	0.933***	[0.0219]
Difficulty finding vacancy			1.065	[0.0520]	1.067	[0.0543]	1.096	[0.0850]	1.115	[0.0886]
Difficulty in app process			1.477	[0.356]	1.503	[0.393]	1.530*	[0.390]	1.517*	[0.368]
Difficulty certifying skills			1.176**	[0.0753]	1.189***	[0.0705]	1.161*	[0.0901]	1.153*	[0.0964]
Middle SES at age 15					0.914	[0.119]	0.913	[0.120]	0.906	[0.120]
High SES at age 15					0.723***	[0.0798]	0.711***	[0.0722]	0.705***	[0.0682]
Unemployed										
Years of education	0.992	[0.0331]	0.984	[0.0371]	0.993	[0.0361]	0.993	[0.0354]	0.998	[0.0378]
Sex (1 = Female)	1.124	[0.304]	1.123	[0.300]	1.105	[0.309]	1.090	[0.305]	1.080	[0.304]
Age	0.826***	[0.0610]	0.829**	[0.0607]	0.836***	[0.0541]	0.832***	[0.0535]	0.711***	[0.0572]
Lack of experience	3.189***	[0.667]	3.302***	[0.763]	3.338***	[0.762]	3.347***	[0.766]	3.261***	[0.788]
Literacy ability	1.145	[0.0958]	1.138	[0.0954]	1.146	[0.102]	1.140	[0.100]	1.137	[0.102]

Table 3 continued

	(1)		(2)		(3)		(4)		(5)	
Noncognitive ability	0.903***	[0.0333]	0.900**	[0.0385]	0.893***	[0.0391]	0.891***	[0.0379]	0.893***	[0.0368]
Difficulty finding vacancy			0.831	[0.118]	0.838	[0.122]	0.869	[0.143]	0.876	[0.141]
Difficulty in app process			1.269	[0.486]	1.314	[0.541]	1.318	[0.543]	1.339	[0.554]
Difficulty certifying skills			0.777	[0.121]	0.766	[0.133]	0.770	[0.135]	0.775	[0.127]
Middle SES at age 15					1.153	[0.259]	1.155	[0.262]	1.133	[0.247]
High SES at age 15					1.441	[0.332]	1.439	[0.323]	1.387	[0.299]
Other human capital controls	YES		YES		YES		YES		YES	
Demographic dontrols	NO		NO		YES		YES		YES	
Regional controls	NO		NO		NO		YES		YES	
Cohort fixed effects	NO		NO		NO		NO		YES	
Pseudo R^2	0.14		0.15		0.15		0.16		0.16	
Observations (n)	7717		7716		7230		7230		7230	

SES = socioeconomic status, STEP = Skills towards Employability and Productivity.
Notes: Base outcome is education–job well matched. Relative risk ratios from a MNL regression are reported. Clustered standard errors on country in brackets. All specifications include a constant term. Other controls for human capital include squared age, self-reported deficiencies in language and computer skills, and dummies for field of training. Civil status, number of siblings at age 12, indicator for being a parent, and dummies for parents' maximum educational attainment comprise the demographic controls. Regional controls include population density, incidence of informal employment, occupational structure (shares of high-skill white collar, low-skill white collar, and crafts and related trade), economic structure (shares of agriculture, industry, and commerce), and education structure (shares of those with postsecondary education and secondary education). Cohort fixed effects are dummies of five year cohorts. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
Source: Authors' estimates based on World Bank STEP surveys.

Figure 2: Actual and Simulated Incidence of Match Outcomes

SES = socioeconomic status, STEP = Skills towards Employability and Productivity.
Source: Authors' estimates based on World Bank STEP surveys.

IV. QUALIFICATION MISMATCH AND WAGES

A. Wage Consequences of Mismatch

Relative to otherwise similar candidates, job seekers facing nontrivial barriers to search are less likely to secure positions for which they are matched. From a wage perspective, it may be possible to quantify the welfare improvements from reducing search costs. This literature has consistently found that the overqualified earn more than workers in the same occupation but make less than those in the job appropriate to their schooling level. Conversely, the underqualified are paid less than workers in the same occupation but make more than similarly educated workers in the job matched to their credentials (Leuven and Oosterbeek 2011). This wage differential may be regarded as the potential gains from improving allocation of labor. In general, the wage differential can be explained through the marginal productivity that an individual obtains in their respective jobs.

This section primarily tests whether search heterogeneity across individuals explain wage differentials among workers of different match outcomes. If the proxies for search only matter to the match outcome and not wages, then the welfare improvements from reducing search costs will be through reallocation rather than through broader adjustments in employment practices. The workhorse wage model of the mismatch literature, can be traced to the work of Duncan and Hoffman (1981). They extend the traditional Mincerian wage equation, decomposing years of schooling acquired S^a into three components: years of schooling required for the job S^r, years of overqualification S^o, and years of underqualification S^u. This results to the following identity:

$$S_i^a \equiv S_i^r + S_i^o - S_i^u$$

The wage model can be expressed as:

$$y_i = \beta_r S_i^r + \beta_o S_i^o + \beta_u S_i^u + \rho X_i + \varepsilon_i$$

where y_i denotes the logarithm of hourly wages and X_i is a vector of explanatory variables such as age, age squared, and gender, including a constant. The success of the model can be credited to its ease of interpretation in terms of several labor market theories. First, standard human capital theory posits that employers fully utilize worker's skills so that only the amount of attained education matters to earnings. Empirically, this is equivalent to the joint equality of schooling returns, $\beta_R = \beta_O = \beta_U$. In contrast, Thurow's (1975) job competition model proposes a labor market in which earnings are not determined by worker's skills or productivity but solely by the requirements of the job ($\beta_O = \beta_U = 0$). Education only serves to rank workers in order of trainability but does not affect wage outcomes. The empirical regularity that overeducated suffer wage penalties ($\beta_R > \beta_O \geq 0$) and undereducated enjoy wage premia ($\beta_U \leq 0$) relative to individuals with similar education suggests that a more realistic model is one in which wages are jointly determined by both worker and job characteristics (Sattinger 1993, Hartog 1986).

B.   Results

Table 4 presents our estimates of the relationship between wages and years of schooling from the pooled sample. The first column contains regression estimates from a standard overeducation–required–undereducation specification with gender, age, and age squared as added explanatory variables. The signs and magnitudes of the coefficients of years required, years of overqualification, and years of underqualification are consistent with findings in the literature.

The coefficients of interest on the returns to years required and years under or over qualified may still suffer from bias due to unobserved skill heterogeneity among workers and omitted characteristics of the job. To examine the role of latent ability and job characteristics, we include a vector of human capital and sector of employment controls that likely determine worker productivity. This includes measures of tenure, cognitive and noncognitive skills, as well as indicator variables for self-reported deficiencies in literacy, computer skills, and experience. In addition, we supply dummies for an index of firm size, informal sector, self-employment, private and public sector wage work. Industry fixed effects are also included.

Unlike previous studies, we are able to observe the task content of the job, which Autor and Handel (2013) have shown to be a crucial determinant of earnings outcomes. Tasks performed on the job are simultaneously determined by job demands and worker characteristics that provide comparative advantage in executing certain tasks. From the results in column 2, we find that accounting for heterogeneity along these dimensions reduces the coefficients of years of overqualification and underqualification by as much as 25%, with the explanatory power driven largely by the inclusion of the task variables. Because these task variables are the outcome of both supply and demand factors, it is difficult to draw conclusive interpretations. A first possibility is that tasks represent units of productivity delivered by the worker such that the rewards (penalties) incurred by overqualified (underqualified) workers relative to well matched individuals in the same job are an artifact of surplus (deficit) of productivity. The remaining unexplained differential could be explained by unmeasured task components. An alternative explanation is that the remaining differential is

correlated with other unobservable components that place maximum bounds on potential productivity that could occur and are related to the firm such as management practices and ability of manager or firm to identify, recruit and utilize certain skills. If this is the case, reallocation of better workers into jobs could have more minimal effects on improved productivity.

Table 4: Wages, Search, and Years of Mismatch Schooling, Pooled Sample

	(1)	(2)	(3)	(4)	(5)
Years required	0.0834***	0.0583***	0.0789***	0.0589***	0.0635***
	[0.00289]	[0.00461]	[0.00392]	[0.00523]	[0.00641]
Years overeducated	0.0473***	0.0339***	0.0447***	0.0349***	0.0351***
	[0.00560]	[0.00470]	[0.00596]	[0.00444]	[0.00324]
Years undereducated	−0.0412***	−0.0266**	−0.0383***	−0.0268**	−0.0290**
	[0.00682]	[0.00978]	[0.00741]	[0.0101]	[0.00996]
Difficulty finding vacancy			0.0336	0.0325	0.0286
			[0.0325]	[0.0424]	[0.0426]
Difficulty in app process			−0.0186	0.0432	0.0557
			[0.0443]	[0.0374]	[0.0306]
Difficulty certifying skills			−0.0477	−0.00763	−0.0179
			[0.0523]	[0.0467]	[0.0450]
Indicator for middle SES at15			0.0515	0.0388	0.0296
			[0.0271]	[0.0323]	[0.0401]
Indicator for high SES at 15			0.157**	0.130**	0.115**
			[0.0433]	[0.0370]	[0.0421]
Country fixed effects	YES	YES	YES	YES	YES
Age and gender controls	YES	YES	YES	YES	YES
Human capital controls	NO	YES	NO	YES	YES
Job characteristic controls	NO	YES	NO	YES	YES
Demographic controls	NO	NO	NO	NO	YES
F(Search costs)			0.47	1.48	1.85
p-value			0.72	0.33	0.26
F(SES at age 15)			8.25	16.14	20.25
p-value			0.03	0.01	0.00
Adjusted R²	0.15	0.19	0.15	0.19	0.20

SES = socioeconomic status, STEP = Skills towards Employability and Productivity.
Notes: The dependent variable in all columns is log hourly wages in PPP. All models include a constant and are weighted by sampling weights. Standard errors in brackets are clustered on country (6 categories). Human capital controls include tenure, cognitive reading and noncognitive skills and an indicator for self-reported deficiency in experience, literacy, and computer skills. Controls for job characteristics include industry fixed effects, dummy for the size of the firm, dummy for self-employed, dummy for informal sector, dummy for private sector wageworker, and dummy for public sector wageworker, and scores for analytical, interpersonal, routine, and manual task intensities following Autor and Handel (2013). Demographic controls include dummies for having spouse and children, indicators for the maximum level of parents' education.
Source: Authors' estimates based on World Bank STEP surveys.

If search costs potentially have more direct ramifications on wages, this could alter the wage distribution beyond the improved allocation of worker-job matches. This could occur if individual heterogeneities in search difficulties potentially are a direct reflection of an individual's unobserved skill and productivity outside of selection into match quality and our observable job characteristics and human capital controls. In columns 3–5 of Table 4, we include our variables for search difficulties. We find that none of the proxies for search cost significantly correlate with wages after including indicators for worker-job qualification match quality. Moreover, the specification combining these variables of search costs with our controls for human capital and job characteristic only marginally changes the significance of the coefficients between columns 1 and 3. However, when we include a full set of controls, the estimates are somewhat higher in absolute value compared to a model with only human capital, demographic, and job variables. This suggests that individual welfare gains from a reduction in

search costs will arise almost entirely from the wage restitution and productivity gains from transitioning into jobs that are more appropriate to an individual's ability (Kampelmann and Rycx 2012). Nevertheless, the set of welfare-improving reallocation will however be limited by the available jobs in the labor market.

A major question is whether the wage consequences to mismatch differ among different economies. Table 5 presents results from the country wage regressions. These reveal differing patterns among different economies. In the Lao PDR where there is a high share of informal employment and more limited share with a tertiary degree, there is no penalty in wages from overqualification and no penalty to underqualification compared to what is required. In Sri Lanka, there is no significant benefit to higher education with workers essentially being paid exactly the amount required by the occupation. Almost all other economies face some penalties in wages for each additional year of overqualification with payoffs that are between one-quarter and one-half of what they would have obtained from entering a job for which they are well matched. These regressions also indicate that search costs and demographics do not explain any of the estimated returns to required schooling and suggest that there could be gains to reducing search frictions and credit constraints in all economies through improved allocation of labor.

Table 5: Relationship between Wages and Years of Mismatch Schooling, Country Samples

	Armenia				PRC (Yunnan)				Georgia			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
S^R	0.0434***	0.0385***	0.0382***	0.0476***	0.0760***	0.0553***	0.0775***	0.0539***	0.114***	0.0396***	0.0960***	0.0438***
	[0.00870]	[0.0127]	[0.00995]	[0.0136]	[0.00748]	[0.0105]	[0.00889]	[0.0108]	[0.0119]	[0.0143]	[0.0137]	[0.0168]
S^O	0.0327**	0.0267*	0.0293*	0.0305*	0.0594***	0.0354***	0.0632***	0.0382***	0.0607***	0.0272*	0.0498***	0.0281
	[0.0140]	[0.0152]	[0.0149]	[0.0165]	[0.0114]	[0.0120]	[0.0120]	[0.0121]	[0.0153]	[0.0162]	[0.0160]	[0.0177]
S^U	0.0134	0.0164	0.0140	−0.00130	−0.0240	−0.0148	−0.0258	−0.0157	−0.092***	−0.069***	−0.082***	−0.0621**
	[0.0206]	[0.0226]	[0.0205]	[0.0213]	[0.0176]	[0.0164]	[0.0172]	[0.0162]	[0.0301]	[0.0252]	[0.0298]	[0.0253]
F(Search costs)			0.88	1.02			0.86	0.55			2.72	1.24
p-value			0.45	0.38			0.46	0.65			0.04	0.29
Adjusted R²	0.113	0.135	0.117	0.111	0.118	0.240	0.129	0.245	0.225	0.311	0.233	0.276

	Lao PDR				Sri Lanka				Viet Nam			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
S^R	0.0631***	0.0179	0.0417***	0.0261	0.109***	0.0718***	0.117***	0.0784***	0.0903***	0.0695***	0.0857***	0.0674***
	[0.0101]	[0.0182]	[0.0148]	[0.0198]	[0.0138]	[0.0245]	[0.0159]	[0.0254]	[0.00678]	[0.0116]	[0.00921]	[0.0116]
S^O	0.0661***	0.0423*	0.0530**	0.0406	0.0400	0.0199	0.0491	0.0283	0.0460***	0.0347***	0.0435***	0.0314**
	[0.0189]	[0.0227]	[0.0210]	[0.0250]	[0.0361]	[0.0378]	[0.0389]	[0.0402]	[0.0121]	[0.0125]	[0.0133]	[0.0135]
S^U	0.0109	0.0410*	0.0304	0.0299	−0.0641*	−0.0286	−0.0601*	−0.0296	−0.049***	−0.042***	−0.046***	−0.0371**
	[0.0246]	[0.0244]	[0.0239]	[0.0256]	[0.0347]	[0.0334]	[0.0330]	[0.0309]	[0.0136]	[0.0156]	[0.0133]	[0.0147]
F(Search costs)			3.84	1.05			1.25	1.64			1.50	1.23
p-value			0.01	0.37			0.29	0.18			0.21	0.30
Adjusted R²	0.116	0.200	0.136	0.177	0.153	0.219	0.150	0.218	0.151	0.187	0.153	0.183

Lao PDR = Lao People's Democratic Republic, PRC = People's Republic of China, STEP = Skills towards Employability and Productivity.
Notes: The dependent variable in all columns is log hourly wages in local currency. We report only OLS estimates for years of required education, years of overeducation and years of undereducation. All models include a constant and are weighted by sampling weights. Heteroskedasticity-robust standard errors are in brackets. Column 1 has age, age squared, and gender as additional explanatory variables. Column 2 extends this to include human capital as well as job characteristic controls. Column 3 adds our proxies for search impediments to the basic column 1 specification, while column 4 corresponds to a specification with search variables as well as controls for human capital and job characteristics.
Source: Authors' estimates based on World Bank STEP surveys.

V. CONCLUSION

Evidence of cross-country qualification mismatch demonstrates that overqualification is even more pervasive in developing Asia than in advanced economies such as the US and other members of the OECD. However, the prevalence of over qualification relative to job requirements masks heterogeneities in skills, jobs, and labor market institutions. Nevertheless we find no evidence to support the idea that current skills are insufficient to meet the demands of the existing labor market. To date, there has been little literature which demonstrates that individual mismatch has ramifications on aggregate productivity or that the current allocation of workers is suboptimal. We make advances on the latter by empirically establishing the link between search costs and mismatches in the labor market in developing countries.

From a policy perspective, our findings indicate scope for a concerted policy response in reducing impediments to search and alleviating credit constraints. Both of these are potentially a far more pressing issue in labor markets in developing countries. This is because in the absence of unemployment insurance, credit constraints, and higher search costs among the poor can result in them more immediately entering jobs for which they are less well matched. This is further exacerbated by the greater absence of easy access to information that is often facilitated through employment service websites and credible skill certification programs that would provide a clearer signal of an individual's ability. The significance of both search costs and socioeconomic status in determining mismatch underscores the potential and economically significant role of reducing impediments to search among the poorer population set. This can ultimately help improve the allocation of labor that leads to gains in average wages and productivity.

Potential policy responses could include small subsidies or incentives targeted at poor, unemployed workers, which reduces search costs and has been shown to effectively raise the intensity of job search both in developed and developing countries (Bryan, Chowdhury, and Mobarak 2014; Philips 2014; Franklin 2015). Field experimental evidence has also shown that greater access to information on vacancies (Dammert, Galdo, and Galdo 2015), provision of career guidance (Behagel, Crépon, and Gurgand 2014), and other active labor market policy interventions (Card, Kluve, Weber 2010) positively affect job-finding rates. Nevertheless, it should be recognized that these programs could have displacement effects, making it harder for noneligible workers to potentially find jobs and may not necessarily justify them as publicly efficient investment (Crépon et al. 2013. Moreover, potential preferences for certain unobserved job types that are not well matched to any jobs that are available could limit developing better matches in the first place (Groh et al. 2015). Embarking on similar studies looking into the failures behind mismatches and full effects of policy interventions would provide a way forward for the literature.

REFERENCES

Acemoglu , D., and F. Zilibotti. 2001. Productivity Differences. *Quarterly Journal of Economics.* 116 (2). pp. 563–606.

Allen, J., and R. van der Velden. 2001. Educational Mismatches versus Skill Mismatches: Effects on Wages, Job Satisfaction and On-the-Job Search. *Oxford Economic Papers.* 53 (3). pp. 434–52.

Altonji, J. G., and C. R. Pierret. 2001. Employer Learning and Statistical Discrimination. *The Quarterly Journal of Economics.* 116 (1). pp. 313–50.

Autor, D., and M. Handel. 2013. Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics.* 31 (2). pp. 59–96.

Baert, S., B. Cockx, and D. Verhaest. 2013. Overeducation at the Start of the Career: Stepping Stone or Trap? *Labour Economics.* 25. 123–40.

Behagel, L., B. Crépon, and M. Gurgand. 2014. Private and Public Provision of Counseling to Job-Seekers: Evidence from a Large Controlled Experiment. *American Economic Journal: Applied Economic.* 6 (4). pp. 142–74.

Berliant, M., R. Reed, and P. Wang. 2006. Knowledge Exchange, Matching, and Agglomeration. *Journal of Urban Economics.* 60 (1). pp. 69–95.

Bryan, G., S. Chowdhury, and A. M. Mobarak. 2014. Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh. *Econometrica.* 82 (5). pp. 1671–748.

Calvo-Armengol, A., and M. O. Jackson. 2007. Networks in Labor Markets: Wage and Employment Dynamics and Inequality. *Journal of Economic Theory.* 132 (1). pp. 27–46.

Card, D., R. Chetty, and A. Weber. 2007. Cash-on-Hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market. *The Quarterly Journal of Economics.* 122 (4). pp. 1511–60.

Card, D., J. Kluve, and A. Weber. 2010. Active Labour Market Policy Evaluations: A Meta-analysis. *The Economic Journal.* 120 (548). pp. F452–F477.

Chevalier, A. 2003. Measuring Overeducation. *Economica.* 70 (279). pp. 509–31.

Chevalier, A., and J. Lindley. 2009. Overeducation and the Skills of UK Graduates. *Journal of the Royal Statistical Society: Series A.* 172 (2). pp. 307–37.

Clark, B., C. Joubert, and A. Maurel. 2014. The Career Prospects of Overeducated Americans. NBER Working Paper No. 20167.

Combes, P., G. Duranton, and L. Gobillon. 2008. Spatial Wage Disparities: Sorting Matters! *Journal of Urban Economics.* 63 (2). pp. 723–42.

Crépon, B., E. Duflo, M. Gurgand, R. Rathelot, and P. Zamora. 2013. Do Labor Market Policies Have Displacement Effects? Evidence from a Clustered Randomized Experiment. *Quarterly Journal of Economics.* 128 (2). pp. 531–80.

Dammert, A., J. Galdo, and V. Galdo. 2015. Integrating Mobile Phone Technologies into Labor Market Intermediation: A Multi-treatment Experimental Design. *IZA Journal of Labor and Development.* 4: 11.

Duncan, G., and S. Hoffman. 1981. The Incidence and Wage Effects of Overeducation. *Economics of Education of Review.* 1 (1). pp. 75–86.

Duranton, G., and D. Puga. 2004. Micro-foundations of Urban Agglomeration Economies. In J. Henderson and J. Thisse, eds. *Handbook of Regional and Urban Economics 4,* pp. 2063–115. Amsterdam: Elsevier.

Fields, G. S. 1975. Rural-Urban Migration, Urban Unemployment and Underemployment, and Job-Search Activity in LDSCs. *Journal of Development Economics.* 2 (2). pp. 165–87.

Franklin, S. 2015. Location, Search Costs and Youth Unemployment. A Randomized Trial of Transport Subsidies in Ethiopia. University of Oxford CSAE Working Paper WPS/2015-11.

Freeman, R. 1976. *The Overeducated American.* Academic Press.

Gottschalk, P., and M. Hansen. 2003. Is the Proportion of College Workers in Noncollege Jobs Increasing? *Journal of Labor Economics.* 21 (2). pp. 449–71.

Green, F., and S. McIntosh. 2007. Is There a Genuine Underutilization of Skills Amongst the Over-qualified? *Applied Economics.* 39 (4). pp. 427–39.

Groh, M., D. McKenzie, N. Shammout, and T. Vishwanath. 2015. Testing the Importance of Search Frictions and Matching through a Randomized Experiment in Jordan. *IZA Journal of Labor Economics.* 4: 7.

Gunther, I., and A. Launov. 2012. Informal Employment in Developing Countries: Opportunity or Last Resort? *Journal of Development Economics.* 97 (1). pp. 88–98.

Hartog, J. 1986. Earnings Functions: Beyond Human Capital. *Applied Economics.* 18 (12). pp. 1291–309.

Heckman, J., J. Stixrud, and S. Urzua. 2006. Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics.* 24 (3). pp. 411–82.

Hsieh, C. T., E. Hurst, C. I. Jones, P. J. Klenow. 2013. The Allocation of Talent and US Economic Growth. NBER Working Paper No. 18693.

Kampelmann, S., and F. Rycx. 2012. The Impact of Educational Mismatch on Firm Productivity: Evidence from Linked Panel Data. *Economics of Education Review.* 31 (6). pp. 918–31.

Korpi, T., and M. Tahlin. 2009. Educational Mismatch, Wages and Wage Growth: Overeducation in Sweden, 1974–2000. *Labour Economics.* 16 (2). pp. 183–93.

Lazear, E., and J. Spletzer. 2012. The United States Labor Market: Status Quo or a New Normal? NBER Working Paper No. 18386.

Lee, L. 1982. Specification Error in Multinomial Logit Models: Analysis of Omitted Variable Bias. *Journal of Econometrics.* 20 (2). pp. 197–209.

Leuven, E., and H. Oosterbeek. 2011. Overeducation and Mismatch in the Labor Market. In E. Hanushek, S. Machin, and L. Woessmann, eds. *Handbook of the Economics of Education, Volume 4.* Elsevier.

Lise, J., and F. Postel-Vinay. 2015. Multidimensional Skills, Sorting, and Human Capital Accumulation. Mimeo.

McGuinness, S. 2006. Overeducation in the Labour Market. *Journal of Economic Surveys.* 20 (3). pp. 387–418.

Mehta, A., J. Felipe, P. Quising, and S. Camingue. 2011. Overeducation in Developing Economies: How Can We Test for It, and What Does It Mean? *Economics of Education Review.* 30 (6). pp. 1334–47.

Neisser, U., G. Boodoo, T. Bouchard, A. W. Boykin, N. Brody, S. Ceci, D. Halpern, J. Loehlin, R. Perloff, R. Sternber, and S. Urbina. 1996. Intelligence: Knowns and Unknowns. *American Psychologist.* 51 (2). pp. 77–101.

Organisation for Economic Co-operation and Development (OECD). 2013. *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills.* OECD Publishing. http://dx.doi.org/10.1787/9789264204256-en

Phillips, D. C. 2014. Getting to Work: Experimental Evidence on Job Search and Transportation Costs. *Labour Economics.* 29. pp. 72–82.

Pierre, G., M. L. Sanchez Puerta, A. Valerio, and T. Rajadel. 2014. STEP Skills Measurement Surveys: Innovative Tools for Assessing Skills. World Bank Social Protection & Labor Discussion Paper No. 1421.

Pissarides, C. 1979. Job Matchings with State Employment Agencies and Random Search. *Economic Journal.* 89 (356). pp. 818–33.

———. 1984. Search Intensity, Job Advertising, and Efficiency. *Journal of Labor Economics.* 2 (1). pp. 128–43.

Quinn, M., and S. Rubb. 2006. Mexico's Labor Market: The Importance of Education-Occupation Matching on Wages and Productivity in Developing Countries. *Economics of Education Review.* 25 (2). pp. 147–56.

Quintini, G. 2011. Right for the Job: Over-Qualified or Underskilled? OECD Social, Employment, and Migration Working Papers.

Robst, J. 2007. Education and Job Match: The Relatedness of College Major and Work. *Economics of Education Review.* 26 (4). pp. 397–407.

Satchi, M., and J. Temple. 2009. Labor Markets and Productivity in Developing Countries. *Review of Economic Dynamics.* 12 (1). pp. 183–204.

Sattinger, M. 1993. Assignment Models of the Distribution of Earnings. *Journal of Economic Literature.* 31 (2). pp. 831–80.

Shimer, R. 2005. The Assignment of Workers to Jobs in an Economy with Coordination Frictions. *Journal of Political Economy.* 113. pp. 996–1025.

———. 2007. Mismatch. *American Economic Review.* 97 (4). pp. 1074–101.

Shimer, R., and L. Smith. 2000. Assortative Matching and Search. *Econometrica.* 68 (2). pp. 343–69.

Sicherman, N. 1991. Overeducation in the Labor Market. *Journal of Labor Economics.* 9 (2). pp. 101–22.

Sicherman, N., and O. Galor. 1990. A Theory of Career Mobility. *Journal of Political Economy.* 98 (1). pp. 169–92.

Spence, M. 1973. Job Market Signaling. *Quarterly Journal of Economics.* 87 (3). pp. 355–74.

Thurow, L. 1975. *Generating Inequality.* Basic Books.

In Search of a Better Match: Qualification Mismatches in Developing Asia

This paper empirically tests the role of search frictions in driving qualification mismatches in the labor market. Using new data from several low-income economies in urban Asia we find that overeducation in less developed labor markets are more pervasive than in more developed economies. Moreover, frictions related to search costs are a crucial determinant of match quality resulting in socially inefficient talent misallocation. Our findings suggest scope for policy interventions that improve worker-job matches with potential gains to wages and aggregate productivity.

About the Asian Development Bank

ADB's vision is an Asia and Pacific region free of poverty. Its mission is to help its developing member countries reduce poverty and improve the quality of life of their people. Despite the region's many successes, it remains home to the majority of the world's poor. ADB is committed to reducing poverty through inclusive economic growth, environmentally sustainable growth, and regional integration.

Based in Manila, ADB is owned by 67 members, including 48 from the region. Its main instruments for helping its developing member countries are policy dialogue, loans, equity investments, guarantees, grants, and technical assistance.

ASIAN DEVELOPMENT BANK
6 ADB Avenue, Mandaluyong City
1550 Metro Manila, Philippines
www.adb.org