LABOR MIGRATION
in the Greater Mekong Sub-region

Does Immigration to Thailand Reduce the Wages of Thai Workers?

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Abstract

In recent years, hundreds of thousands of unskilled immigrants have arrived in Thailand, prompting concerns about detrimental effects on Thai wages. Empirical studies from developed countries suggest that any effects are likely to be small, but the relevance of these studies to a developing country such as Thailand is unclear. We construct estimates of the effects of immigration on Thai labor market outcomes, by exploiting geographic variation in migrant concentrations. Data on migrants are obtained from a 2004 registration campaign. To avoid biases created by the tendency for migrants to go to places with high wages, we instrument migration on distance to the Myanmar border. We find that immigration does reduce the wages of Thai workers, and that this effect is stronger than is normally observed in developed countries. We also find that immigration has no effect on Thai employment rates.

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1. Introduction

According to a recent opinion poll, 83 percent of Thais believe that to immigration in Thailand reduces the wages of native workers.[2] Most empirical studies suggest that immigration does indeed reduce native wages, but that the effect is small. Pooling results from 18 studies, Longhi, et al. (2005) estimate that a one percentage point rise in the share of migrants in the workforce leads to a mere 0.119 percent reduction in native wages. All the studies used by Longhi et al were, however, carried out in developed countries, and their relevance to a developing country such as Thailand can be questioned. Since Thais do not have social insurance to rely on when withdrawing from the labor market, for instance, the supply response to immigration may be weaker, and the wage response stronger, than in developed countries. Similarly, since minimum wages are not binding for most Thai workers (Falter, No date), they do not put a floor on wage effects from immigration.

Assessing the labor market impacts of immigration to a developing country is rarely feasible, because such assessments require adequate data on numbers of migrants, including undocumented migrants, and such data are seldom available. Thailand is, however, a partial exception. Beginning in the 1990s, Thailand has received hundreds of thousands of migrants from Cambodia, Laos, and Myanmar, and smaller numbers from China, Vietnam, and elsewhere, so that migrants now constitute roughly 4 percent of Thailand's working-age population. Although some migrants from Myanmar are fleeing conflict, immigration to Thailand also reflects wage differentials: Thailand's GDP per capita exceeds GDP per capita in Cambodia, Laos, and Myanmar by about the same multiple that GDP per capita in the United States exceeds GDP per capita in Mexico. Virtually all migrants from Cambodia, Laos, and Myanmar have entered the country illegally. In 2004, the Thai government allowed these migrants to register for permits giving them the right to live and work in Thailand for one year. Because the terms offered were relatively favorable, the registration probably captured a significant proportion of migrants from these countries. The registration data thus offer a rare opportunity to evaluate the effect of immigration on the wages of natives in a developing country.

Like most empirical studies of the labor market effects of immigration, the analysis in this paper exploits geographical variation in migrant intensity. Essentially we test whether, all else equal, areas with unusually high concentrations of migrants have unusually low wages. The test is complicated by the fact that migrants are attracted to areas with high wages. We address this issue by instrumenting migrant concentrations on distance to the Burmese border. We obtain a statistically significant negative relationship between immigration and native wages. The effect is stronger than is typically found in developed countries. We also find that immigration has no effect on Thai employment rates.

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[2] *Unpublished tables from a poll of 4,148 Thais conducted by Assumption University between 25 November and 1 December 2006, supported by the International Labour Organization and the United Nations Development Fund for Women.*

2. Predictions and evidence regarding immigration and wages

In a simple model of the labor market effects of immigration, the addition of immigrants to the labor force shifts the labor supply curve outward, which leads to a reduction in wages, which induces natives to reduce their labor supply. In the long run, the labor demand curve also shifts outwards, as firms invest in new capital for the additional workers. Under constant returns to scale, wages and native labor supply eventually return to their pre-immigration levels (Altonji and Card 1991). Labor market effects become more complicated, however, when factors such as the characteristics of immigrants, native migration patterns, and labor market institutions are incorporated into the analysis.

The extent to which immigrants actually compete with natives depends on the skills of immigrants and natives, and regulations governing immigrants. In the United States and Europe, immigrants span the whole range of education levels (Angrist and Kugler 2003; Card 2005), while in Thailand almost all immigrants from the main sending countries of Cambodia, Laos, and Myanmar have limited education. Many migrants to Thailand also have difficulty speaking the Thai language. In the United States and Europe, the majority of migrants are legally permitted to reside in the country[3], while in Thailand most migrants have a much weaker legal position, in theory and in practice. Migrants who register but had entered the country illegally are still technically in violation of Thailand's Immigration Act, and the government's long-term stance towards immigrants remains uncertain. Possession of a work permit provides only partial protection against deportation (Pearson et al. 2006: 27-29), and registered migrants are prohibited from performing skilled occupations. Moreover, as discussed below, only about 60 percent of all immigrants were registered in 2004. The weak legal status of migrants presumably deters employers from investing in their skills, or promoting them. This means migrants most resemble unskilled Thais, though they differ even from them.

When an area receives immigration, native workers may react by moving out of the area, or by refraining from moving in. Compensatory migration by natives would reduce the outward shift in the labor supply curve in the immigrant-receiving areas, but shift labor supply curves elsewhere in the country. This could explain why studies that use geographical variation in immigrant shares to

[3] *Undocumented migrants constitute around 30 percent of all migrants in the United States [23, p2], and around 16 percent in Europe [22, Table 1.2]*

identify labor market effects have generally found small effects. Evidence on the importance of compensatory migration is, however, mixed. Card and DiNardo (2000) find no evidence for the existence of compensatory migration in the United States. Hatton and Tani (2005) find evidence of substantial compensatory migration in Britain, but only when they restrict their sample to southern England. When Borjas (2003) tests for the labor market effects of immigration using variation across age-groups, rather than geographical areas, he finds strong effects. He attributes the strength of these effects to the fact that his estimates are not subject to downward biases because of compensatory migration. However, Friedberg's (2001) study of Israel in the early 1990s is almost as well protected from biases due to compensatory migration, since she uses variation in migrant share across occupations, yet she finds that immigration inflows equivalent to 12 percent of the Israeli population had no effect on native wages.

3. Data and methods

3.1 Main data sources

Our estimates of migrant numbers are based on data from a registration campaign for migrants from Cambodia, Laos, and Myanmar in 2004.[4] Altogether, 0.82 million migrants obtained work permits, of whom 13 percent were from Cambodia, 13 percent from Laos, and 74 percent from Myanmar. Only migrants aged 15 and over were permitted to register. Two-thirds of migrants were aged less than 30 years old, and 45 percent were women. Many migrants and employers avoided the registration because they did not wish to identify themselves to the authorities or to spend the necessary time and money. In some places, the process was also poorly publicized. However, the registration did provide migrants with some protection from police harassment, and improved their chances of accessing health care and schooling for themselves and their dependants (Pearson 2006: 27-29). It also enrolled far more migrants than similar campaigns before or after (Huguet and Punpuing 2005: 34). In 2005, the Ministry of Interior asked village heads to report on the number of migrants from Cambodia, Laos, and Myanmar, registered or unregistered, living in their communities. This process produced a national total of 1.44 million migrants aged 15 and over[5], implying that the 2004 registration had captured around 60 percent of all working-age migrants. This is low compared with the approximately 90 percent coverage of illegal immigrants achieved in the US Population Census in 2000 (Card and Lewis 2005: 4). But it is

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[4] *The Thai Ministry of Labor kindly provided us with unit record data for these migrants, giving age, sex, nationality, and district of registration.*

[5] *Unpublished tabulations provided by the Ministry of Interior. Unfortunately, the Ministry of Interior were unable to provide us with figures on migrant numbers by district by nationality, so were were unable to use their data in our analysis.*

considerably better than the approximately 10-20 percent coverage achieved by the Thai Population Census in 2000.[6] Moreover, the analyses presented in this paper are based on the relative distribution of migrants across districts, rather than absolute numbers, which helps minimize biases due to under-reporting.

Our main source of data on Thai workers is four rounds of the Labor Force Survey carried out by the Thai National Statistical Office in 2004. We exclude people who were not in the labor force or were outside the main working ages of 15-59 years. We also exclude people employed by the government or state-owned enterprises, because these people do not compete with migrants, and their wages are unlikely to be affected by immigration. Questions on birthplace were asked in the second round of the survey. We exclude the 0.8 percent of respondents from this round who give a birthplace other than Thailand. It is not possible to identify non-Thais in the other three rounds, but the number is unlikely to be high enough to have a material effect on our results. These exclusions leave 354,921 observations covering virtually all of the country. The most important limitation of the Labor Force Survey data is that employers, the self-employed, unpaid family workers, and members of cooperatives are not asked to state a wage. Private employees, who do provide wage data, make up 41 percent of the total. We return to this issue below. Table 1 provides summary statistics for the whole sample and for private employees.

Table 1: Characteristics of respondents in Labor Force Survey sample (percent)

	Private employees	Whole sample
Female	46.0	49.1
Age 15-29	38.3	25.7
Age 30-44	44.0	44.4
Age 45-59	17.6	29.9
0-6 years school	44.4	37.1
7+ years school	55.6	62.9
Private employee	100.0	40.7
Employer	0.0	4.0
Member of cooperative	0.0	0.1
Self-employed	0.0	33.3
Unpaid family worker	0.0	21.9
Observations	144,296	354,921

[6] The 2000 Thai Population Census identified 118,077 people of all ages born in Cambodia, Laos, and Myanmar, and usually resident in Thailand, regardless of legal status (authors' tabulations based on the 20 percent sample). Yet the following year, 568,245 working-age migrants from these three countries registered to work in Thailand, despite a fee equivalent to 1-2 months' wages (Huguet and Punpuing 2005: 34). The Thai National Statistical Office is aware of the poor coverage of migrants in the 2000 Census and, with funding from the World Bank, is developing new procedures to improve coverage in the 2010 Census.

3.2 Initial model

Our initial model is

$$\overline{w}_d = \alpha + \gamma\, m_d + e_d \qquad (1)$$

where $\overline{w}_d$ is mean log wages[7] of Thai workers in district d in 2004, and m_d is 'migrant intensity'. Migrant intensity is defined as $log(M_d/(M_d+T_d))$ where M_d is the number of registered migrants, and T_d the number of Thais, aged 15 to 59 in district d in 2004. When referring to districts, we use 1990 rather than 2004 borders, because data for some of the control variables in subsequent specifications are only available for 1990 borders.

Our definition of migrant intensity implies that log wages are proportional to the log of the migrant share. Most previous studies have used the migrant share itself, rather than the log share. Our decision to use the log share is motivated by the linear bivariate relationship between log shares and wages (Figure 2), and the near-linear relationship between log shares and distance to the border (Figure 1). In addition, the log share has useful properties when there is significant under-reporting of migrants. If m_d^* is true migrant intensity and r_d is the proportion of migrants who register, then $m_d = m_d^* + r_d$. The proportion registering, r_d, is an omitted variable in Equation 1 and subsequent models. As discussed in Section 3.2.2, instrumenting on distance to the border can reduce biases due to the omission of r_d from the model in the same way that it reduces biases due to other omitted variables such as demand for labor.

The median number of observations per district for native wages is 95.5, though 5 percent of districts have 11 observations or fewer. Estimates of the district-level wage in districts with small numbers of observations are subject to substantial sampling error. However, these errors should not lead to biased coefficient estimates, since the district-level wage is an outcome variable, not an explanatory variable. Dropping the districts with low numbers of observations might reduce the standard errors on the coefficient estimates, but it might also create a selection bias. We therefore retain all districts. The wide range in numbers of observations does, however, lead to heteroskedasticiy in the error term e_d. All standard errors and statistical tests presented in the paper are therefore heteroskedasticity-robust.

[7] *Hourly wages, including payments in kind, overtime, and bonuses.*

Equation 1 and all subsequent models make no reference to the length of time that migrants have been in Thailand. There are no reliable longitudinal data on migrants in Thailand that could be used to model labor market adjustment over time. Many local labor markets had presumably partly adjusted to the presence of migrants by 2004. Our coefficient estimates therefore, unavoidably, reflect an unknown mix of short-run and long-run effects.

3.3 Human capital of Thai workers

District-level differences in mean wages for Thai workers reflect, among other things, differences in the human capital of these workers. Following Card (2005), we purge mean wages of the effects of differences in human capital by replacing $\overline{w}_d$ with a regression-adjusted value w_d. Let w_{id} be the log wage, and z_{id} a vector of human capital variables[8], for person i in district d, and let c_d be a district-level fixed effect. The revised version of Equation 1 is

$$w_d = \alpha + \gamma M_d + e_d \qquad (2)$$

where the w_d's equal the fixed effects from individual-level equations of the form

$$w_{id} = \alpha + \beta_z z_{id} + c_d + e_{id} \qquad (3)$$

3.4 Endogeneity

If the decision to come to Thailand is motivated, at least in part, by the prospect of earning higher wages, then it would be surprising if migrants' decisions of where to live within Thailand were not also affected by wage differentials. Migrant intensity M_d in Equation 2 should therefore be treated as endogenous.

An initial step towards allowing for endogenous migration is to add a vector of variables X_d that attempts to capture determinants of wage levels.

$$w_d = \alpha + \gamma m_d + \beta X_d + e_d \qquad (4)$$

The first variable in X_d is the distance, in thousands of kilometers, from the center of district d to Bangkok, to capture the concentration of economic activity on the capital city. All remaining variables in X_d refer to the year 1990, before the

[8] *The vector consists of potential experience, gender, eight categories of education, and a full set of interactions between these terms.*

onset of large-scale immigration from neighboring countries, to avoid biases due to reverse causation from migration to X_d. One of these, (log) Gross Provincial Product (GPP) for the district which district d is located, was obtained from the National Economic and Social Development Board. The others were calculated by us from the 20 percent sample of the 1990 Population Census. The first census variable is the proportion of the population in district d living in urban areas. The second is the proportion of households in district d that belong to the bottom 40 percent of the household wealth distribution, where household wealth is calculated by applying a principal components analysis to household asset data (Filmer and Pritchett 2001). The remaining variables measure district-level employment structure using the proportion of private employees working in International Classification of Industries 1958 one-digit industries.[9]

We make further allowance for endogenous migration by instrumenting migrant intensity on distance to the border. Let m_{cd} be 'country-specific' migrant intensity, defined in the same way as m_d, except that only migrants from country c appear in the numerator. Figure 1 shows Myanmar-specific migrant intensity versus the distance from each district to the Myanmar border. There is a strong relationship between migrant intensity and distance to the border. Regressing migrant intensity on distance gives a good fit, but, because of the curvature evident in Figure 1, regressing on the square root of the distance gives an even better fit.[10] Regressing Myanmar-specific migrant intensity on the square root of distance to the Myanmar border and on X_d gives a coefficient estimate for the square root of distance of -0.218 ($p < 0.001$). An equivalent regression for Cambodian migrants gives similar results, while a regression for Laos gives a weaker relationship with distance to the border. In all three cases, migrant intensity has a strong positive relationship with GPP per capita, and a strong negative relationship with the percent of households in the bottom 40 percent of the wealth distribution (results not shown).

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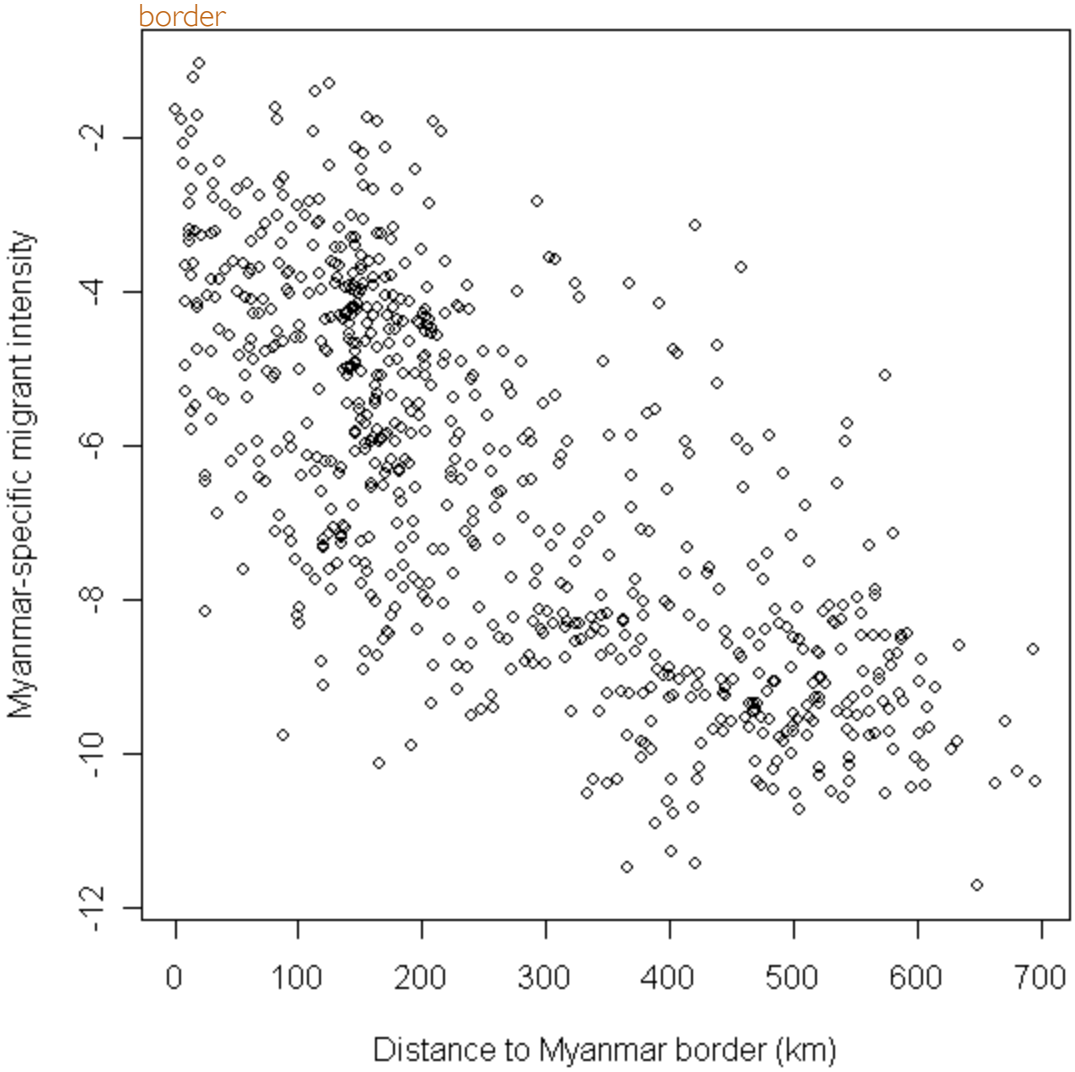
[9] *The omitted employment category is all other industries.*

[10] *Regressing on the square root also gives a slightly better fit than regressing on distance and distance squared, with or without control variables.*

Figure 1: Myanmar-specific migrant intensity versus distance to the Myanmar border



The negative relationship between distance to the border and migrant intensity owes something to transport costs. Migrants sometimes pay the equivalent of several months' wages to be smuggled into Central Thailand (Caoutte, Archavanitkul, and Pyne 2000: 71-3). The particular form of the relationship also suggests that a diffusion process may be operating. An approximately linear negative relationship between migrant intensity and distance implies that migrant numbers decline exponentially with distance. This is what would be expected if, because of 'friends and neighbors' effects, new migrants tend to move to districts that already contain migrants, or that are adjacent to districts already containing migrants.[11]

[11] *A simple way to derive an exponential decline from a friends and neighbors effect is to treat districts as equally spaced points along a line, and let migration evolve according to the following rules: in period 0, there are no migrants; in period 1, one migrant moves to district 1; in period t, t> 1, the number of migrants in district d grows by a factor of 1+ r if district d previously contained at least one migrant, grows to 1 if district d previously contained no migrants but was next to a district with a migrant, and remains at 0 otherwise. Under these assumptions, the number of migrants declines exponentially with distance.*

The somewhat weaker relationship between distance and migrant intensity for Lao migrants probably reflects the fact that Lao language and culture are close to those of Thais, so that Lao migrants can travel more easily than other migrants and rely less on migrant networks.

Whatever the exact processes that account for the association between migrant intensity and distance, it is plausible that these processes generate variation in migrant intensity that, after controlling for distance to Bangkok, GPP per capita, household poverty, and employment structure, is only weakly correlated with demand for labor. Instrumenting on distance to the border should reduce biases due to endogenous migration.

As noted in Section 3.2, another possible source of endogeneity is variation in registration coverage. Much less is known about the determinants of registration coverage than is known about the demand for labor, so deciding which variables are likely to be correlated with registration coverage is unavoidably speculative. Border districts tend to contain newly-arrived migrants and 'daytrippers' who commute across the border, so coverage may be lower in these areas. We include a dummy variable b_d that takes a value of 1 if a district is on the border. Variables that have already been included to control for labor demand may also help control for registration coverage. For instance, the distance-to-Bangkok variable would control for any tendency for more remote areas to enforce the rules less vigilantly, and the employment variables would control for differences in coverage rates across different industries. Since there is no compelling reason why registration coverage should vary systematically with distance to the border once factors such as proximity to the border and employment structure have been controlled for, instrumenting on distance to the border should provide at least some protection against endogenous registration coverage.

Implementation of the instrumental variables model is complicated by the fact that we have used logs to define migrant intensity. Each of the country-specific migrant intensities is well modeled by a linear function of variables such as (the square root of) distance to the country's border. However, the relationship between overall migrant intensity and the three country-specific migration intensities is highly non-linear: $M_d = log\{\sum_c exp(m_{dc})\}$. Rather than proceed with a complicated non-linear model, we construct instrumental variable estimates only for migrants from Myanmar. As noted above, migrants from Myanmar account for 74 percent of all registered migrants.

4. Results

4.1 Main results

Table 2 presents the results for our main analysis, correlating wages of Thais against migrant intensity. Results for the first four columns were obtained using ordinary least squares. As can be seen in column 1, and also in Figure 2, the raw district-level relationship between migrant intensity and wages is strongly positive. Regression-adjusting for differences in the human capital of Thai workers, as is done in column 2, reduces the strength of the relationship slightly. Adding variables to control for labor demand and registration rates in column 3 reduces the strength of the relationship considerably, though the relationship remains positive. The model of column 4 is identical to that of column 3, except that 'migrant intensity' refers only to migrants from Myanmar, and the 'border' dummy refers only to the Myanmar border. The numbers of districts used in the analysis falls between columns 3 and 4 because 41 districts contain zero migrants from Myanmar, and therefore do not have values for migrant intensity. Using just Myanmar migrants reduces the coefficient on migrant intensity slightly.

Figure 2: Mean log wages versus migrant intensity

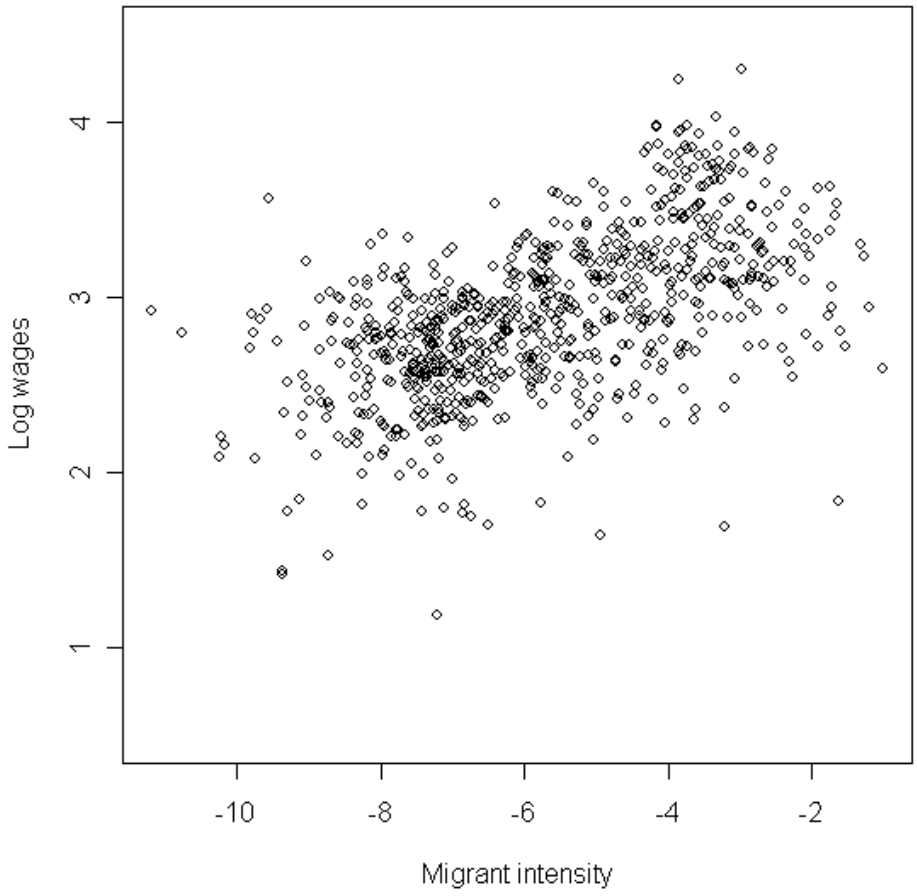


Table 2: Determinants of wages

Coefficient	(1)	(2)	(3)	(4)	(5)
Migrant intensity	0.139	0.113	0.034	0.026	-0.023
	(0.007)	(0.006)	(0.007)	(0.006)	(0.011)
Border	-0.432	-0.331	-0.148	-0.184	-0.062
	(0.040)	(0.029)	(0.028)	(0.039)	(0.045)
1000 km from Bangkok			0.123	0.103	0.171
			(0.044)	(0.044)	(0.044)
(Log) GPP per capita			0.210	0.207	0.315
			(0.019)	(0.019)	(0.028)
Urban			0.043	0.016	0.005
			(0.030)	(0.029)	(0.032)
Poor households			-0.471	-0.476	-0.660
			(0.064)	(0.069)	(0.075)
Emp. agriculture			-0.661	-0.334	-0.159
			(0.371)	(0.351)	(0.383)
Emp. commerce			-0.821	-0.268	-0.324
			(0.464)	(0.452)	(0.469)
Emp. construction			-0.842	-0.473	-0.402
			(0.388)	(0.370)	(0.400)
Emp. electricity			2.515	-4.332	-7.849
			(1.527)	(3.230)	(3.492)
Emp. manufacturing			-0.567	-0.168	-0.058
			(0.380)	(0.358)	(0.387)
Emp. mining			-1.112	-0.714	-0.262
			(0.555)	(0.554)	(0.633)
Emp. services			-0.804	-0.459	-0.315
			(0.390)	(0.371)	(0.405)
Emp. transport			-1.227	-0.923	-0.820
			(0.395)	(0.497)	(0.510)
Constant	3.749	0.119	-0.096	-0.460	-1.178
	(0.044)	(0.032)	(0.380)	(0.358)	(0.426)
Adj. R-squared	0.410	0.425	0.603	0.602	0.557
Districts	758	758	758	717	717

Column 5 also refers to Myanmar migrants, but here migrant intensity is instrumented on distance to the border. Doing so reverses the sign of the coefficient on migrant intensity. There is now a statistically significant negative relationship between migrant intensity and the wages of Thai workers (p =0.041; as discussed in Section 3.2 all standard errors and tests reported in the paper are heteroskedacity-robust.) A coefficient value of -0.023 implies that a 10 percent increase in the number of immigrants leads to a 0.23 percent reduction in the wages of Thai workers.

4.2 Extensions and robustness tests

Migration into one labor market can have spillover effects on adjacent labor markets through, for instance, trade or the migration flows of native workers (Borjas 2003). Moreover, even in the absence of spillovers, a mismatch between the boundaries of districts and the boundaries of labor markets can induce spatial correlations between districts (Anselin and Bera 1998: 239). We investigate spatial dependency by estimating a model with spatial lags,

$$w_d = \alpha + \gamma\, m_d + \beta\, X_d + p\, W w + e_d \qquad (5)$$

where w is a vector containing all values of w_d, W is a matrix of weights, and p is the spatial correlation coefficient. The model is analogous to an AR(1) model in time-series statistics. Matrix W is constructed in two steps: first, each element w_{ij} of W is set equal to 1 if district j borders district i and 0 otherwise; second, the rows of the matrix are normalized so that each row sums to 1. The coefficient p governs the rate at which correlations die off with distance. The presence of w on the right hand side means that Equation 5 cannot be estimated using ordinary least squares. The usual alternatives are to use maximum likelihood methods, or to instrument on spatial lags of X_d. An advantage of the instrumental variables approach is that heteroskedasticity-robust standard errors can be calculated (Anselin and Bera 1998: 258-60). However, neither approach is designed for the situation where elements of X_d are endogenous.[12] We therefore estimate two versions of Equation 5: one with migrant intensity itself, and the other with our instrument for migrant intensity, the square root of distance to the Myanmar border. The second version does not yield a coefficient on migrant intensity, but it is informative about the direction and statistical significance of the wage-migration relationship, while being robust to endogenous migration. Both versions yield estimates of p that can be used to assess the importance of spatial dependence.

[12] *For the instrumental variables approach, see Kelejian and Prucha (1998: 101).*

Table 3: Models that allow for spatial dependency

Coefficient	(1)	(2)	(3)
Migrant intensity	0.0232		-0.0215
	(0.0059)		(0.0213)
Sqrt distance to border		0.0059	
		(0.0023)	
Border	-0.1958	-0.0699	-0.0498
	(0.0373)	(0.0429)	(0.0603)
1000 km from Bangkok	0.1253	0.1330	0.0002
	(0.0431)	(0.0413)	(0.0001)
(Log) GPP per capita	0.2081	0.2726	0.2223
	(0.0204)	(0.0187)	(0.0537)
Urban	0.0269	0.0159	0.2374
	(0.0281)	(0.0289)	(0.1341)
Poor households	-0.5112	-0.6429	-0.8824
	(0.0658)	(0.0599)	(0.2040)
Emp. agriculture	-0.2966	-0.2523	-1.2846
	(0.3241)	(0.3393)	(1.2791)
Emp. commerce	-0.3947	-0.5141	-2.2262
	(0.4065)	(0.4140)	(1.9142)
Emp. construction	-0.4486	-0.3970	-1.6633
	(0.3351)	(0.3567)	(1.3579)
Emp. electricity	-4.5802	-7.2487	-49.4773
	(3.1882)	(3.1358)	(29.4162)
Emp. manufacturing	-0.1329	-0.1501	-1.1276
	(0.3316)	(0.3439)	(1.2805)
Emp. mining	-0.6490	-0.2550	-1.5882
	(0.5275)	(0.5664)	(2.1379)
Emp. services	-0.4197	-0.4012	-1.4460
	(0.3430)	(0.3606)	(1.3110)
Emp. transport	-0.8110	-0.7546	-0.1587
	(0.4900)	(0.4864)	(1.5486)
Constant	-0.5015	-0.9058	0.2299
	(0.3428)	(0.3585)	(1.3032)
Spatial correlation coefficient	-0.0059	-0.0003	
	(0.0463)	(0.0488)	
Adj. R-squared			0.7257
N	717	717	72

An alternative way to incorporate spillovers is to base the analysis on large geographical units (Borjas 2003). We accordingly re-estimate Equation 4 using provinces rather than districts.

Next we investigate whether the relationship between immigration and Thai wages varies according to the skill levels and gender of Thai workers. We use the same explanatory variables as Equation 4. We also continue to use districts as the unit of analysis, and to instrument migration on distance to the border. However, we calculate the regression-adjusted wage w_d for sub-samples of private employees, based on age (15-29 versus 30-59), education (0-6 years versus 7 or more), and gender.

Our analysis of the effect of immigration on labor supply also retains the same basic setup while using alternative outcome variables. First we look at district averages for hours worked during the previous week by private employees. Then we look at the proportion of each district's labor force (other than government and state-owned enterprise employees) who worked during the previous week. Both these measures, like all our outcome variables, are regression-adjusted for differences in human capital.

As well as influencing labor supply, immigration could potentially influence the choice between formal and informal employment. If, for instance, immigration depresses the wages of Thai private employees, but does not depress the wages of other workers, then Thais might move from formal-sector to informal-sector employment. To test for this sort of movement, we estimate a model in which the outcome variable is the proportion of the district labor force (other than government or state-owned enterprise employees) working as private employees.

As a final robustness test, we re-estimate our wage model with the wages of government and state-owned enterprise employees, rather than private employees, as the outcome variable. Since migrants do not compete with state sector workers, the coefficient on migrant intensity should be zero. A non-zero coefficient would suggest that our estimation strategy has not dealt satisfactorily with omitted variables (Angrist and Krueger 2001).

To test whether immigration leads to compensatory migration by natives, we have estimated a conditional logit model using migration data from the 2004 Labor Force Surveys. However, in the course of constructing the model, we noticed some implausible features of the data such as substantial net out-migration from Bangkok that undermine our trust in the findings. We intend to pursue the topic of compensatory migration in future research, and do not present any results here.

The results presented in Table 3 suggest the omission of spatial dependency from our basic model does not have a material effect on the results. Column 1 of Table 3 shows the basic spatial lags model. This model, while allowing for spatial dependency, ignores the endogeneity in migrant intensity, which is why the relationship between migration and wages is positive. As apparent in column 2, however, there is a positive and significant relationship between wages and (the square root of) distance to the Burmese border, implying a negative relationship between wages and the exogenous component of migrant intensity. More importantly, the spatial correlation coefficients in columns 1 and 2 are both tiny and statistically insignificant. The implication is that, when predicting wages in district d, nothing is gained by taking into account conditions in neighboring districts. As can be seen by comparing column 3 of Table 3 and column 5 of Table 2, using provinces rather than districts increases the standard error for migrant intensity substantially, but has little effect on the point estimate. Together, the results in Table 3 imply that incorporating spillovers and associated effects has a negligible impact on our main findings.

Figure 3: Differences in the strength of the relationship between immigration and wages

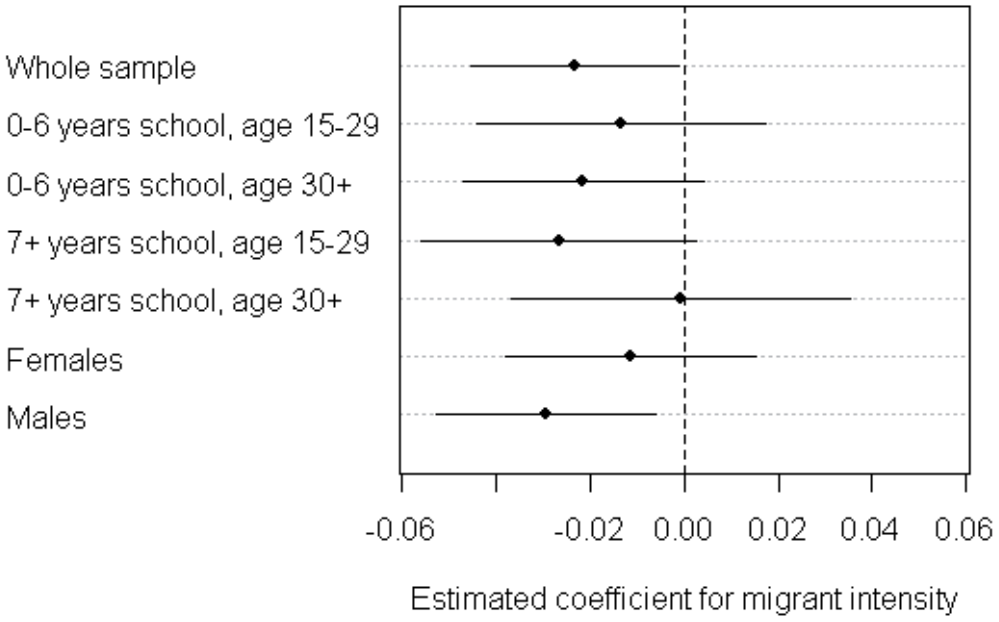


Figure 3 summarizes the results from the six regressions testing whether the relationship between immigration and wages varies across sub-samples of Thai workers. The figure also shows the full-sample results from column 5 of Table 2. The black dots denote point estimates and the horizontal lines denote 95 percent confidence intervals. The point estimates suggest that migrants have no effect at all on the wages of older, well-educated Thai workers, which is plausible. However the point estimates also suggest that most adversely affected group is young, well-educated Thai workers, which is implausible. Moreover, all the estimates are imprecise, as indicated by the wide confidence intervals, so it would be prudent not to place too much weight on these results. Immigration seems to have a bigger impact on men's wages than on women's wages, though again the imprecision of the estimates indicates the need for caution in interpreting the results.

Table 4: Coefficient on migrant intensity for other labor market outcomes

Dependent variable	Estimate	Std. Error
Worked in last week	0.004	(0.001)
Hours worked by private employee	0.420	(0.190)
Is private employee	-0.003	(0.004)
Wages for government employee	0.001	(0.007)

The first two rows of Table 4 show coefficients on migrant intensity from our models of labor supply. In both cases, immigration has a statistically significant positive effect on Thai labor supply. Both effects are, however, economically insignificant. Based on the estimated coefficients, the arrival of an extra 100,000 immigrants would increase the probability that a Thai worked in the last week by 0.0003, and would increase the time spent working by 2 minutes per week.[13]

There appears to be no relationship between migrant intensity and the proportion of workers who are private employees. Immigration does not seem to induce shifts in the relative share of formal and informal employment.

There is also no relationship between migrant intensity and the wages of government workers. Theory suggests that there should be no relationship, so the null result provides some reassurance as to the appropriateness of our estimation strategy.

5. Discussion

Our preferred specification for estimating the effect of immigration on Thai wages is the instrumental variables model without spatial lags. The coefficient on migrant intensity from this specification is -0.023. This number comes from regressing log wages on the log migrant share. Most previous studies have regressed log wages on the migrant share itself. To make our number approximately comparable to those of previous studies, we need to divide it by the mean migrant share across districts (Longhi et al. 2005). The mean migrant share is 0.013.[14] Dividing -0.023 by 0.013 gives a value of -1.769. This is a much stronger effect than Longhi et al.'s (2005) median value of -0.119, though it is lower in absolute value than the estimates of -3 to -4 that Borjas (2003) obtains for the United States.

The strength of the wage effect in Thailand is almost certainly related to the absence of an employment effect. Thai labor markets appear to have adjusted to immigration through a reduction in wages rather than a reduction in employment rates or hours. This presumably reflects the fact that most Thais cannot afford to withdraw from the labor force, and the absence of a binding minimum wage. The fact that immigrants to Thailand have lower skills and a much more precarious legal status than immigrants to developed countries may also have contributed to the relatively strong wage effect and weak employment effect. However, we lack any direct evidence on mechanisms.

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[13]The employment and hours equations are both in semi-log form, so the change in the dependent variable (measured in natural units) equals the coefficient estimate times the proportional change in the independent variable. Based on the assumption that there are approximately 1.5 million working-age migrants in Thailand, an extra 100,000 migrants represents a proportional increase of 0.067. This gives 0.004 x 0.067 ≈ 0.0003 and 0.420 x 0.067 ≈ 0.0281 hours ≈ 2 minutes.

[14]This is the mean Myanmar-specific migrant share. We use the Myanmar-specific migrant share since the instrumental variables model uses Myanmar-specific migrant intensities. The mean of district-level migrant shares is considerably lower than the mean migrant share for the whole country since there is a strong positive correlation between migrant share and district population size.

Strictly speaking, our wage results apply only to the 41 percent of non-government workers who are private employees. However, if immigration had reduced the wages of private employees but not workers in the informal sector, then Thai workers could be expected to shift from the formal sector to the informal sector. We find no indication that shifts from formal to informal sectors has been occurring. This is indirect evidence that immigration has depressed incomes in the informal sector, and not just the formal sector.

Assuming that Thailand's immigrant population has been growing by about 7 percent per year (enough to double the immigrant population in 10 years), then our results for wages imply that immigration has cut 0.1 to 0.2 percentage points off the annual wage growth of Thai workers. This is trivial compared to Thailand's nearly 10 percent annual wage growth in the early 1990s, but looms larger compared to the slow growth in recent years. Nevertheless, our results for labor supply suggest that immigration has not had any detrimental effects on Thai employment rates.

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