Does immigration to Thailand reduce the wages of Thai workers?

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Data from a Thai campaign to register irregular migrants offer a rare opportunity to study the labor market effects of immigration in a developing country. We use the registration data, plus census and survey data on Thais, to study how immigration has affected wages, employment, and domestic labor migration in Thailand. Essentially we test whether, all else equal, Thais living in places with more immigrants have different labor market outcomes from other Thais. We allow for endogenous migration, whereby immigrants are disproportionately attracted to areas with higher wages, by using distance to the Myanmar border as an instrument for migrant intensity. We allow for geographical spillovers by estimating our model at two levels of geographical aggregation, and by constructing a model with spatial lags. We also test whether Thais avoid migrating into areas that have received more immigrants. Our results suggest that immigration has reduced the wages of Thais. We find no evidence that immigration reduces employment, or that it affects internal migration.

Introduction

Eighty-three percent of Thais believe that immigration to Thailand reduces local wages[1]. Results from empirical studies from developed countries suggest that any reductions are likely to be small. A meta-analysis of 18 such studies suggests that a one percentage point rise in the share of migrants in the workforce depresses native wages by only 0.119 percent (Longhi, Nijkamp, and Poot 2005: 472). But it is hazardous to extrapolate from these studies, since developing countries differ from developed ones in ways that are likely to affect the migration-wage relationship. For instance, in Thailand, as in many developing countries, minimum wages are rarely binding (Falter, No date), and a substantial proportion of the local workforce does the dirty or dangerous jobs typically associated with migrants.

Evaluating the labor market impacts of immigration to a developing country is typically impossible because of the absence of adequate data on migrants, including irregular migrants. 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. Although these flows include people who are essentially refugees, 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 neighboring countries have entered the country illegally. In 2004, the Thai government allowed Cambodian, Lao, and Myanmar 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 appears to have captured a significant proportion of migrants in Thailand. The registration data thus offer a rare opportunity to evaluate the effect of immigration on the wages of natives in a developing country.

We identify the labor market effects of immigration using geographical variation in migrant intensity. This is the most common strategy used in developed-country studies, and is the one most suited to our data on migrants, a single cross-section with detailed geographical information.. 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 using distance to the border as an instrument for migrant intensity. We also test whether the effects are strongest for low-skilled Thai workers, and examine other labor market outcomes such as employment. If native workers are deterred from migrating into areas that have received large numbers of immigrants, this can transmit the labor market impacts to other parts of Thailand. We therefore test whether immigration affects internal migration by Thais. Our results suggest that immigration does lower Thai wages, but does not lower employment rates or effect internal migration.

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

Theory and evidence on immigration and wages

In the most basic 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 on regulations faced by immigrants. In the United States and Europe, immigrants span the entire range of education levels (Angrist and Kugler 2003; Card 2005). In Thailand, almost all immigrants from the main sending countries of Cambodia, Laos, and Myanmar have limited educations. 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[2], while in Thailand most migrants have a much weaker legal position. 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 (Pearson et al 2006: 27-29). Registered migrants are also prohibited from performing skilled occupations. Moreover, as discussed below, only about a half 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 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 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 time and 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

[2] Undocumented migrants constitute around 30 percent of all migrants in the United States (Passel 2005: 2), and around 16 percent in Europe (Mansoor 2007: Table 1.2]

(2001) study of Israel in the early 1990s is almost as well protected from the 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.

Data and methods

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[3]. 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 obtain work permits. Two-thirds of migrants were aged less than 30, 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). Officials and non-governmental organizations typically assume that the registration campaign covered around half the irregular migrants in the country. 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 considerably better than the 10-20 percent coverage achieved by the Thai Population Census in 2000[4]. Moreover, the analyses presented in this paper are based on the relative distribution of migrants across districts, rather than absolute numbers, which helps reduce biases due to under-reporting.

[Table 1 here]

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 government employees[5], 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

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

[4] The 2000 Thai Population Census identified 70,173 usual residents aged 15 and over who were born in Cambodia, Laos, or Myanmar, and did not have Thai citizenship (our calculations from the 20 percent sample, using sample weights.) This number should, in principle, have included irregular migrants, since the census frame makes no reference to the legal status of residents. However, the following year, 568,245 migrants aged 15 and over 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.

[5] Here and throughout the paper we include employees of state-owned enterprises with government employees.

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. 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 39.6 percent of the (weighted) total. We return to this issue below. Table 1 provides summary statistics for the whole sample and for private employees.

Initial model

Our initial model is

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

where $\overline{w}_d$ is mean log wages[6] of Thai workers in district d in 2004, m_d is 'migrant intensity', and b_d is a vector of dummy variables indicating whether district d is on the Cambodian, Lao, or Myanmar borders. 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. All districts are defined by 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).

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 is an omitted variable in Equation 1 and subsequent models. The border dummies in Equation 1 attempt to capture some of the variation in proportions registering. Border areas contain disproportionately high numbers of newly-arrived migrants, and migrants who commute for work who are less likely to be captured in registration data.

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 bias our coefficient estimates since wages are an outcome variable, rather than an explanatory variable. The variability in numbers of observations can, however, be expected to lead to heteroskedasticiy in the error term, so all standard errors and statistical tests presented in the paper are heteroskedasticity-robust.

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[6] Hourly wages, including payment 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.

Human capital of Thai workers

District-level differences in the mean wages of 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[7], for person *i* in district *d*, and let c_d be a district-level fixed effect. The revised version of Equation 1 is

$$w_d = \alpha + \gamma m_d + \delta b_d + e_d \qquad (2)$$

where w_d is the fitted values for c_d in

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

Endogeneity

If the decision to come to Thailand is motivated, at least in part, by the prospect of earning higher wages, then migrants' decisions of where to live within Thailand should also reflect wage differentials. Migrant intensity m_d in Equation 2 should therefore be treated as endogenous.

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

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

The first variable in X_d is the distance, in hundreds of kilometers, from the center of district *d* to Bangkok, to capture the concentration of economic activity on the capital city. The next variable is (log) Gross Provincial Product (GPP) per capita in the province where district *d* is located[8]. The data refer to 1990, before large-scale migration to Thailand had begun, to avoid biases that would arise if migration were influencing GPP.

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[7] The vector consists of age, age squared, years of schooling, years of schooling squared, gender, and a full set of second-order interactions between these terms.

[8] The GPP data were obtained from the website of the National Social and Economic Development Board.

Next come the proportion of the population living in urban areas, and the proportion of households that belong to the bottom 40 percent of the household wealth distribution. Both measures were calculated by us from the 20 percent sample of the 1990 Population Census. Household wealth was calculated by applying a principal components analysis to household asset data (Filmer and Pritchett 2001). A further set of variables calculated from the 1990 Census give the proportional distribution of the employed population by industry, where industry is defined according to the one-digit codes for the 1958 International Classification of Industries. Finally, we include a dummy variable taking a value of 1 if district *d* is in the South of Thailand (as defined by the National Statistical Office.) As is well-known to Thai economists, labor market outcomes differ systematically between the South and the rest of Thailand: for instance, wages are unexpectedly high. We do not attempt to explain these differences here.

Our next step in addressing endogenous migration is to instrument migrant intensity on distance to the border. Let m_{cd} be 'country-specific' migrant intensity, defined in the same way as m_{cd}, except that only migrants from country *c* appear in the numerator. Figure 1 shows Myanmar-specific migrant intensity versus distance to the Myanmar border. There is a strong relationship, with a hint of curvature. In a model predicting Myanmar-specific migrant intensity, containing border dummies and X_d, distance and distance-squared have an F-statistic of 170 (results not shown.) An equivalent regression for Cambodian migrants gives similar results, while a regression for Laos gives a weaker relationship. 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 that are poor.

[Figure 1 here]

The negative relationship between distance to the border and migrant intensity owes something to transport costs. Migrants sometimes must pay the equivalent of several months' wages to be smuggled into Central Thailand (Caoutte, Archavanitkul, and Pyne 2000: 71-3). However, 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[9]. The somewhat weaker relationship between distance and migrant intensity for Lao migrants may reflect the fact that Lao language and culture are close to those of Thais, which means that Lao migrants can travel more easily than other migrants and rely less on migrant networks.

[9]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 time 0, there are no migrants. In time 1, one migrant moves to district 1. In time $t > 1$, 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.

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 therefore help reduce biases due to the endogeneity of migration.

Implementation of the instrumental variables model is complicated by the use of logs in the definition of migrant intensity. Each of the country-specific migrant intensities is well modeled by a linear function of variables such distance to the country's border. However, the relationship between overall migrant intensity and the three country-specific migration intensities takes the highly non-linear form of $m_d = \log\left(\sum_c \exp(m_{cd})\right)$. 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.

Any labor market impacts from immigration to Thailand are likely to be largest for low-skilled Thai workers, since these workers compete most directly with immigrants. We therefore construct a 'low-skill' version of the adjusted-wages variable, in which individuals are only included in Equation 3 if they have six or fewer years of schooling. Similarly, we test for gender differences using adjusted-wage variables calculated from males only and females only.

Results

Main results

Table 2 presents results for wages of private employees. 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 in column 2 reduces the strength of the relationship slightly. Adding variables to control for labor demand in column 3 reduces the strength considerably, though the relationship remains positive. Column 4 is identical to column 3, except that overall migrant intensity is replaced by Myanmar-specific migrant intensity. The number of observations drops by 42, because of districts that do not have any migrants from Myanmar, and which therefore do not have a defined value for Myanmar migrant intensity. All four OLS models have negative coefficient estimates for the Myanmar border dummy, though only the first two have negative estimates for the Lao or Cambodian border.

[Figure 2 and Table 2 here]

Moving to an instrumental variables specification in column 5 reverses the sign on migrant intensity. Because migrant intensity is defined as a log share, there is a log-log relationship between wages and migrant numbers. The coefficient on migrant intensity in column 5 implies that a 10 percent increase in migrant numbers is associated with a 0.185 percent reduction in local wages. Contrary to expectations, the point estimate for low-skilled Thai workers in column 6 is virtually identical to the estimate for all workers in column 5. In both cases, the Myanmar border dummy becomes statistically indistinguishable from zero: the overall negative relationship between migration and wages is sufficient to explain the low wages along the Myanmar border.

Using the same approach to model wages for males and females gives an estimated coefficient of -0.0189 (SE 0.0093) for males and -0.0143 (SE 0.0123) for females.

Extensions and robustness tests

Migration into one labor market can have spillover effects on adjacent labor markets through, for instance, trade or migration 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,

$$w_d = \alpha + \gamma m_d + \delta b_d + \beta X_d + \rho W_d' w + \varepsilon_d \tag{5}$$

where w is a vector containing all values of w_d, W_d is a vector of weights, and ρ is the spatial correlation coefficient. W_d is constructed by setting the i-th element equal to 1 if district i shares a border with district d and 0 otherwise, and then normalizing so that W_d sums to 1. The spatial correlation coefficient ρ governs the rate at which correlations die off with distance.

The spatial lags model is not designed for situations where explanatory variables are endogenous (Kelejian and Prucha 1998: 101). We therefore replace migrant intensity with distance to the Myanmar border. A positive coefficient on distance would imply a negative relationship between migration and wages, though without providing information about the magnitude of the relationship. The presence of w on the right hand side means that Equation 5 cannot be estimated using ordinary least squares. Instead we use instrument on spatial lags of X_d, which allows heteroskedasticity-robust standard errors to be calculated (Anselin and Bera 1998: 258-60)[10]. We use as dependent variables the wages of all private employees and the wages of low-skilled private employees.

An alternative way to incorporate spillovers is to use larger geographical units (Borjas 2003). We re-estimate models 5 and 6 from Table 2 using provinces rather than districts.

[Table 3 here]

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[10] Estimation was carried out using the *stsls* function in the package *spdep* for the statistical language *R* (Bivand 2008).

The spatial lags models, shown in columns 1 and 2 of Table 3, fail to detect any relationship between wages and distance to the Myanmar border. Most of the coefficient estimates from the spatial lags models are smaller in absolute value than those of Table 2, but detecting a relationship with distance to the border is perhaps especially difficult because distance is highly correlated among neighboring districts. Without the negative relationship between wages and migration or distance to Myanmar, the coefficients on the Myanmar border dummy again become negative.

The instrumental variables models based on provinces, shown in columns 3 and 4, give a completely different result. The coefficients on migrant intensity are about three times as large as those from Table 2, albeit with much larger standard errors.

Next we examine the effect of immigration on labor supply, measured by (i) hours worked during the previous week by private employees, and (ii) the proportion of the labor force (other than government employees) who were employed during the previous week. Both supply measures are regression-adjusted for human capital and then regressed on the same explanatory variables as column 5 of Table 2, again using distance and distance squared to the Myanmar border as instruments for migrant intensity. Table 4 shows the results. To save space, coefficient estimates for control variables have been omitted from the table. As can be seen in column 1, Thai employment rates appear to be positively related to migrant intensity. Given the semi-log specification of column 1, the coefficient on migrant intensity implies that a 10 percent increase in migrant numbers is associated with a 0.055 percentage point increase in Thai employment rate. There is a hint of a positive relationship between migrant intensity and hours worked, but it is far from being statistically significant.

[Table 4 here]

The wage results shown in Table 2 refer only to private employees. This raises the question of how immigration is affecting other workers, such as those in the informal sector. An indirect way of assessing the effects on other workers is to examine the relationship between migration and the sectoral distribution of Thai workers. If migration has a different effect on private employees than on other types of workers, then migration should induce Thais to leave or enter private employment. We test for this possibility by regressing the percentage of the labor force (other than government employees) working as private employees against the same set of variables as earlier, again instrumenting on distance to the border As can be seen in column 3 of Table 4, migration appears to have a negative relationship with private employment. The estimated coefficient and the semi-log form of the specification imply that a ten percent increase in migrant numbers is associated with a 0.1 percentage point reduction in the proportion of the district labor force working as a private employee.

All previous models have excluded government employees on the grounds that migrants do not compete with government employees. As a robustness test, re-estimate our wage model using (regression-adjusted) government wages as the dependent variable. A non-zero coefficient on migrant intensity would suggest that our estimation strategy is flawed (Angrist and Krueger 2001). The estimated coefficient, shown in column 4, turns out to be indistinguishable from zero.

Finally, we apply the same approach to testing whether immigration has induced compensatory migration by Thais. Unlike the labor force variables, our data for the migration variables come from the 20 percent sample of the 1990 and 2000 censuses, which provide sufficiently large samples to allow migration variables to be constructed at the district level[11].We calculate the percentage of each district's Thai population (other than government employees) who stated that they had migrated into the district for work within the previous two years. The mean value for 1990 is 0.85 percent and for 2000 is 1.00 percent. We also calculate a second version of this variable that includes only Thai migrants with 6 years of schooling or less. We use district-level differences between 1990 and 2000 as our outcome variable; differencing should eliminate biases due to fixed characteristics that make some districts less attractive or more attractive to Thai migrants. We assume that immigrant flows during the 1990s followed a similar geographical pattern to that of 2004 and treat a positive coefficient on distance to the Myanmar border, or a negative coefficient on a border dummy, as evidence that Thais have avoided migrating into districts receiving large numbers of immigrants. The results are shown in columns 5 and 6 of Table 4. Neither column provides support for the idea that immigration has affected internal migration by Thais.

Discussion

The 83 percent of Thais who believe that immigration reduces local wages are, according to our results, correct. Our preferred instrumental-variables specification, shown in column 5 of Table 2, has a coefficient on migrant intensity of -0.0185. Contrary to expectations, restricting the analysis to low-skilled workers gives essentially the same result. Immigration seems, if anything, to have slightly raised employment rates, and to have had no effect on hours worked.

There are a number of limitations to our analysis. Immigrants are clearly attracted to districts with higher wages, which can bias our estimate towards zero. Instrumenting on distance to the Myanmar border should have reduced this bias, but may not have removed it completely. One interpretation of the apparent positive relationship between immigration and employment rates is that we have not completely eliminated the effects of endogeneity..

[11] Also, in exploratory work, we found apparent inconsistencies in migration data from the Labor Force Survey.

A potential weakness of analyses based on geographical variation is that they fail to take account of spillovers to areas with low numbers of migrants. Our analyses incorporating spillovers give mixed results. Adding spatial lags eliminates the relationship between distance to the Myanmar border and wages, though this is perhaps an unreasonably difficult test, and, in any cases, the spatial lags model implies that wages are unexpectedly low along the Myanmar border. Estimating the basic model using provinces instead of districts has the opposite effect: it raises the point estimate for migrant intensity, though the new estimate is imprecise.

If Thais were avoiding migrating into areas with concentrations of migrants, this would mask the labor market effects from immigration by diffusing the labor supply shock. However, we find no evidence that Thai internal migration has in fact responded to immigration. At the same time, Thais do appear to have responded to immigration by slightly reducing their participation in private employment. This suggests that immigrants compete most directly with private employees. It also suggests that movement between sectors may have played a role analogous to migration in transmitting labor supply shocks more widely across the economy.

An important limitation of our data is the extensive, but poorly understood, under-reporting of migrant. If, despite controls for things such as distance to Bangkok and employment structure, and border dummies, registration rates are still systematically related to distance to the Myanmar border, then our estimates will be biased.

In summary, it would be unwise to place too much weight on the precise figure of -0.0185. The hint of endogeneity and the large coefficient in the provinces model both suggest that the true effect may be larger, at least for private employees. However, it is still useful to compare this figure with estimates obtained from developed countries. Most such estimates have come from regressing log wages on migrant share. Our estimate can be made approximately comparable to these by dividing by the mean migrant share (Longhi et al 2005). The mean share of Myanmar migrants is 0.016, so our estimate translates to about -1.2 from previous studies. This is a considerably larger in absolute value than Longhi et al's (2005) median value of -0.119, though smaller than the values of -3 to -4 found by Borjas (2003).

Even so, the impact of immigration on overall labor market outcomes in Thailand should not be overstated. A coefficient on migrant intensity of -0.0185 implies that immigration sufficient to double migrant numbers in 10 years would reduce wage growth by one tenth of a percentage point per year.

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Table 1 – Descriptive statistics for Labor Force Survey sample (percent)

	Private employees		Whole sample	
	Unweighted	Weighted	Unweighted	Weighted
Female	45.9	43.2	53.3	49.9
Age 15-34	55.0	61.0	44.2	52.7
Age 35-59	45.0	39.0	55.8	47.3
6 years school or less	55.2	53.4	54.4	55.1
Private employee	100.0	100.0	35.7	39.6
Employer	0.0	0.0	3.5	3.0
Self-employed	0.0	0.0	29.0	28.2
Unpaid family worker	0.0	0.0	19.1	20.6
Government employee[1]	0.0	0.0	12.7	8.5
N	145,959	13,010,267	527,705	42,914,961

[1]Includes employees of state-owned enterprises.

Table 2 – The relationship between migration and wages of private employees

	(1) Raw wage, all (OLS)	(2) Adj wage, all (OLS)	(3) Adj wage, all (OLS)	(4) Adj wage, all (OLS)	(5) Adj wage, all (IV)	(6) Adj wage, low skill (IV)
Migrant intensity	0.1450**	0.1166**	0.0224**			
	(0.0073)	(0.0056)	(0.0065)			
Myanmar migrant intensity				0.0115*	-0.0185*	-0.0188*
				(0.0049)	(0.0092)	(0.0096)
On Myanmar border	-0.6140**	-0.4499**	-0.1532**	-0.1397**	-0.0439	-0.0855
	(0.0675)	(0.0492)	(0.0397)	(0.0399)	(0.0482)	(0.0519)
On Cambodian, Lao border	-0.3111**	-0.2496**	-0.0167	0.0296	0.0182	-0.0196
	(0.0409)	(0.0314)	(0.0327)	(0.0336)	(0.0346)	(0.0373)
Distance to BKK, 100km			-0.0447**	-0.0458**	-0.0511**	-0.0462**
			(0.0055)	(0.0056)	(0.0063)	(0.0064)
(Log) GPP per capita			0.1240**	0.1340**	0.1863**	0.2087**
			(0.0196)	(0.0184)	(0.0203)	(0.0213)
Proportion urban			0.0100	0.0057	-0.0137	-0.027
			(0.0222)	(0.0225)	(0.0248)	(0.0257)
Proportion poor			-0.3330**	-0.3483**	-0.4282**	-0.4448**
			(0.0663)	(0.0650)	(0.0685)	(0.0718)
Employed in commerce			-0.3238*	-0.3458*	-0.2242	0.1082
			(0.1468)	(0.1435)	(0.1677)	(0.2214)
Employed in construction			1.0917*	1.1192*	1.5110**	0.9095
			(0.4649)	(0.4674)	(0.4760)	(0.4685)
Employed in electric			-0.1436	-0.2879	-0.5043	-0.7988*
			(0.2910)	(0.2805)	(0.3160)	(0.3841)
Employed in manufacturing			0.3081**	0.2994**	0.2979**	0.3237**
			(0.0955)	(0.0941)	(0.0975)	(0.1024)
Employed in mining			-1.8911**	-1.8028**	-0.9679	-1.5434*
			(0.6355)	(0.5856)	(0.6229)	(0.7187)
Employed in services			0.4012**	0.4397**	0.5119**	0.4322**
			(0.1241)	(0.1204)	(0.1311)	(0.1368)
Employed in transport			-0.9942	-1.0575	-2.2586**	-1.7678*
			(0.6008)	(0.6042)	(0.6691)	(0.7923)
Employed in other			2.6139**	2.7819**	2.6789**	1.4547
			(0.8599)	(0.8381)	(0.8745)	(0.9029)
South			0.4040**	0.4058**	0.4689**	0.5318**
			(0.0312)	(0.0328)	(0.0391)	(0.0399)
(Constant)	3.7834**	0.1341**	-0.6387**	-0.7143**	-1.0370**	-1.1816**
	(0.0434)	(0.0315)	(0.0917)	(0.0822)	(0.1084)	(0.1124)
Adjusted R-squared	0.4211	0.4325	0.6713	0.6838	0.6697	0.6915
N	760	760	760	718	718	717

Note – the omitted category for the employment variables is employment in agriculture.
*Significant at 5% level. **Significant at 1% level. All standard errors are heteroskedasticity-robust.

Table 3 – Models of wages allowing for spatial dependency

	(1) All, districts (spatial lag)	(2) Low-skill, districts (spatial lag)	(3) All, provinces (IV)	(4) Low-skill, provinces (IV)
Myanmar migrant intensity			-0.0566*	-0.0504*
			(0.0251)	(0.0255)
Distance to Myanmar border (100km)	0.0050	0.0003		
	(0.0060)	(0.0063)		
On Myanmar border	-0.0505	-0.0961**	0.0599	0.0175
	(0.0336)	(0.0361)	(0.0653)	(0.0660)
On Cambodian, Lao border	0.0014	-0.0076	0.0018	0.0057
	(0.0302)	(0.0309)	(0.0371)	(0.0368)
Distance to Bangkok (100km)	-0.0284**	-0.0283**	-0.0596**	-0.0568**
	(0.0068)	(0.0070)	(0.0129)	(0.0125)
(Log) GPP per capita	0.0869**	0.1051**	0.2235**	0.2046**
	(0.0199)	(0.0222)	(0.0489)	(0.0503)
Proportion urban	0.0337	0.0202	0.0996	0.048
	(0.0213)	(0.0222)	(0.0732)	(0.0761)
Proportion poor	-0.3683**	-0.3580**	-0.5049*	-0.6083**
	(0.0604)	(0.0624)	(0.2209)	(0.2186)
Employed in commerce	-0.2970	-0.0462	1.1387	1.4833
	(0.1517)	(0.2031)	(0.9301)	(0.9555)
Employed in construction	0.9331*	0.7764*	4.2784**	3.0102*
	(0.3971)	(0.3798)	(1.4290)	(1.4063)
Employed in electric	-0.1391	-0.5365	0.5237	1.2822
	(0.2768)	(0.3202)	(4.0947)	(3.7929)
Employed in manufacturing	0.1816*	0.1813*	0.8493**	0.9364**
	(0.0786)	(0.0866)	(0.3054)	(0.3151)
Employed in mining	-0.749	-1.4417**	-7.5262*	-7.5629*
	(0.5142)	(0.5412)	(3.2895)	(3.4983)
Employed in services	0.2877**	0.2206	1.4192**	1.2271
	(0.1060)	(0.1145)	(0.5405)	(0.6478)
Employed in transport	-0.9328	-0.6162	-17.3680**	-14.6603*
	(0.5047)	(0.5931)	(5.4096)	(6.0873)
Employed in other	1.0470	0.5168	5.0849	2.4833
	(0.7734)	(0.7883)	(2.6400)	(2.7469)
South	0.2832**	0.3448**	0.5122**	0.5910**
	(0.0415)	(0.0496)	(0.0852)	(0.0840)
(Constant)	-0.4624**	-0.5792**	-1.4512**	-1.3651**
	(0.0947)	(0.1082)	(0.3305)	(0.3446)
Spatial correlation coefficient	0.3537**	0.3259**		
	(0.0760)	(0.0812)		
Adjusted R-squared			0.8303	0.8456
N	767	767	73	73

Note – the omitted category for the employment variables is employment in agriculture.
*Significant at 5% level. **Significant at 1% level. All standard errors are heteroskedasticity-robust.

Table 4 – Relationship between migration and labor market outcomes and migration

	(1) Percent employed (IV)	(2) Hours last week (IV)	(3) Percent private employees (IV)	(4) Government wages (IV)	(5) Change in % migrants, all (OLS)	(6) Change in % migrants, low-skill (OLS)
Myanmar migrant intensity	0.5527**	0.3378	-0.9675*	-0.0060		
	(0.1574)	(0.1972)	(0.4509)	(0.0078)		
Distance to Myanmar border (100km)					0.0093	0.0064
					(0.0264)	(0.0180)
On Myanmar border	-0.8458	1.5468	-0.0578	-0.0576	-0.116	-0.0942
	(0.7194)	(0.8968)	(2.4055)	(0.0370)	(0.1875)	(0.1326)
On Cambodian, Lao border	0.4958	0.5145	-2.4009	-0.0023	0.1404	0.0052
	(0.4011)	(0.8842)	(1.3245)	(0.0263)	(0.0960)	(0.0654)

Note – these coefficients estimates were obtained from models with the same control variables as Table 2. *Significant at 5% level. **Significant at 1% level. All standard errors are heteroskedasticity-robust.

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

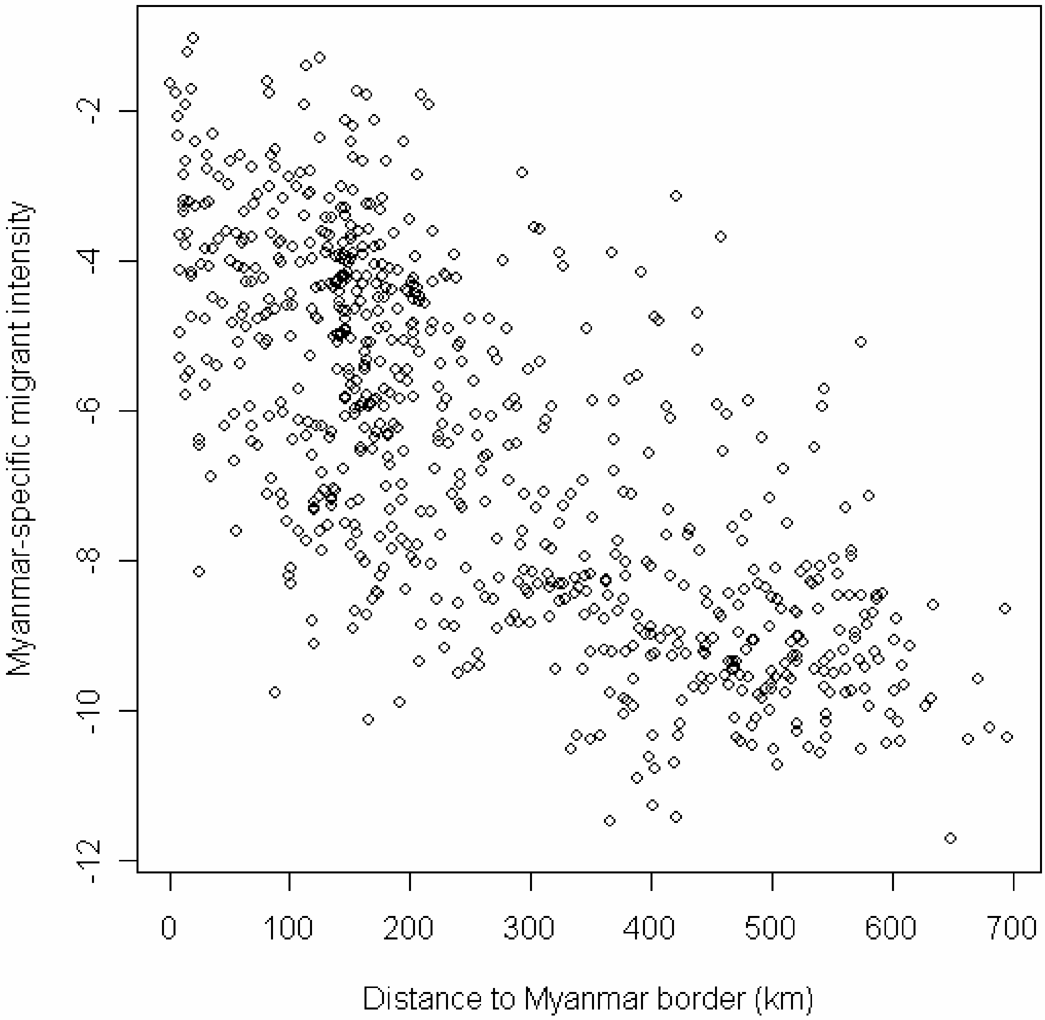

Figure 2 – Wages versus migrant intensity