Impact of Internal Migration on Labor Market Outcomes of Native Males in Thailand

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I. Introduction

The 2009 Human Development Report (UNDP 2009) estimates that at least 740 million people worldwide are internal migrants, that is, almost four times the number who have moved internationally. Despite this, perhaps because movements within borders often go undocumented, the literature on internal migration and its consequences on local labor markets is much smaller than the voluminous literature on international migration.[1] In this regard, a key difficulty in measuring the impact of internal migration is the endogeneity of migration flows. More precisely, net migration is likely to be correlated with economic conditions in each region, making it difficult to identify the impact of migration on variables, such as the wage and employment level, which also depend on such factors. In this study we use exogenous climatic shocks to identify the impact of internal migration on labor market outcomes at destination provinces in Thailand.

In particular, we analyze the effects of interprovincial migration on wages and employment in Thailand using the Thai Labor Force Survey for the period 1991–2000, a rich data set that allows us to identify semiannual migration flows between Thai provinces.[2] Our main contribution relies on the fact that, in contrast to previous studies that have focused mainly on employment

We are grateful to two anonymous reviewers for comments. Contact the corresponding author, Frank Walsh, at frank.walsh@ucd.ie.

[1] See Lucas (1997) or Mendola (2012) for reviews of the literature on internal migration in developing countries or De Brauw, Mueller, and Lee (2014) for a review of the literature on urban-rural migration in sub-Saharan Africa.

[2] We focus on males because employment rates are much higher than for females and because estimation for the latter is further complicated by needing to model the labor supply decision.

Electronically published September 20, 2017
 0013-0079/2017/6601-0006$10.00

probabilities and on income or hourly wages, we investigate the impact on weekly wages and hours worked. Arguably the focus on weekly wages and hours worked could be crucial because examining only hourly wages or weekly wages ignores the potential link between remuneration and hours worked. Many previous studies focus on a single measure of earnings—hourly, weekly, or perhaps daily or annually—without explicitly considering that hours may vary.[3] This may be an important omission. For example, we will see in this study that there are no statistically significant effects of inward migration on the hourly wage of natives but substantial effects on weekly wages, driven by a reduction in hours.

The large literature on migration and its impact tends to implicitly assume that hours per worker are fixed or do not explicitly consider variation in hours. It may well be that sometimes this is a reasonable assumption. In some cases there may be little variation in hours in response to migration.[4] We show here, though, that for the Thai case this is not so, implying that it is always important to check.

In a standard competitive model with fixed hours, if we assume labor supply is inelastic, a shift in labor supply induces a fall in wages of substitute workers, and the percentage change in wage from a percentage change in labor supply is just the inverse of the elasticity of labor demand.[5] The standard competitive model where hours are variable is a little more complicated. The firm's production function depends on both the number of workers and the hours per worker, while the workers labor supply decision is based on a wage hours bundle rather than just the wage. This model originally developed by Lewis (1969) is the precursor of the compensating differentials model, and equilibrium is a set of tangencies in wage hours space between worker's indifference curves and the firm's isoprofit curves. Kinoshita (1987) develops the comparative static properties of this model, and Strobl and Walsh (2011) use a simplified version of Kinoshita's model with homogeneous workers and firms to analyze minimum wages and hours worked. In this simple model the number of workers supplying labor and the number of workers demanded at the mar-

[3] For example, if we examine recent studies that study the impact of internal migration, Kleemens and Magruder (2014) look at employment and income per hour but do not analyze weekly hours, and Maystadt et al. (2014) look at the employment probability and monthly income. Prominent studies that look at international migration (e.g., Aydemir and Borjas 2007) look at annual, monthly, and weekly income and the share of weeks worked but not weekly hours, while Ottaviano and Peri (2012) similarly focus on wage changes without considering hours explicitly, and Friedberg (2001) considers the impact of a large influx into the Israeli labor market on hourly wages of natives.

[4] Indeed, it may well be that the authors of the studies checked for variation in hours and did not report this if there was little variation.

[5] See Borjas (2013) for a recent very clear exposition of the analytics of the model with fixed hours.

ket level are a function of the level of worker utility, which as noted above depends on both wage and hours. For this reason we can no longer think of an estimate of the hours elasticity from a change in migration as the inverse elasticity of demand for workers, as in the simple case where hours are fixed. Of course, this does not mean that we cannot compare our estimates of the elasticity of hours from a change in migration with those from other studies; we do this in the results section below. Rather, our results show that hours per worker vary substantially, and the theoretical model we would use to understand these results would be different from the way we would interpret estimated elasticities in a model with fixed hours.

To isolate the impact of migration on hours worked and weekly wages in Thailand, we focus on short-term supply shock–induced movements of labor between provinces—more specifically, using the methodology developed by Boustan, Fishback, and Kantor (2010) and similarly employed in a developing country context by Strobl and Valfort (2015) and Maystadt et al. (2014). This approach explicitly relies on exogenous variation in weather between provinces to construct arguably plausible instruments for interprovincial migration flows that take into consideration the geographic distance between sending and receiving provinces. The underlying rationale rests on the fact that, particularly in developing economies, weather conditions might induce a spatial reallocation of the relatively mobile input labor.[6]

Arguably, Thailand—in particular during our sample period—constitutes an ideal case study for the task at hand. Standards of living, economic and cultural structures, and growth rates differ widely among provinces, while the labor market tends to be flexible and is generally characterized by very low unemployment rates. Additionally, climate in Thailand is dominated by tropical monsoons and high temperatures that vary widely across space and time.[7] Moreover, Thailand is one of the earliest Southeast Asian economies to implement an export-led growth strategy, the consequence of which is an increase in rural-urban migration, especially to the service sector in Bangkok (Guest 2003). These factors set the context for potentially large amounts of internal migration

[6] For instance, Yang and Choi (2007) examine how remittances sent by migrants respond to income shocks experienced by Philippine households. The authors use rainfall shocks as instrumental variables for income changes and show that in households with migrant members, exogenous income declines are partially covered by foreign remittances. More particularly, households with migrant members enjoy a flat consumption path compared with households without migrants for whom consumption responds strongly to income shocks.

[7] For example, the Southwest monsoon, which starts between May and June, announces the beginning of the rainy season and lasts to October. The dry season is shorter in the south, and rainfall varies significantly from one region to another, depending on latitude and landforms. The northeast region, with a longer dry season and a laterite soil, has a limited agricultural activity.

within the country, particularly because—as noted by Guest (2003)—migrants in Thailand benefit from good transportation links and well-established social networks that result in migration being low cost. As a matter of fact, the National Migration Survey of Thailand (Chamratrithirong et al. 1995) and the Thailand Migration Report (2011) showed these labor movements to be indeed substantial. One may want to note in this regard that while seasonal migration from rural to urban areas is an important element in this and tends to swell the population of Bangkok during the wet season, there are also substantial flows across all regions and in both seasons, as we will show below. Additionally, Chalamwong (1998) points out that after the 1997 economic crisis, return migrants tended to head back to the poorest region of the country—the northeast—followed by the north, central, and south regions. There is also evidence of the absorptive capacity of return migrants from urban areas to rural farm activities (Chamratrithirong 2007). However, despite the 1997 crisis, which may have altered migration patterns for seasonal and short-term workers, there have been no signs of a slowdown in the rates of internal migration.[8]

The remainder of the paper is organized as follows. In Section II we review the literature. Section III outlines our data set, and Section IV presents the empirical specification and econometric results. Section V concludes the paper.

II. Review of the Literature

A. Literature on Effects of Migration on Labor Market Outcomes

The literature on the impact of international migration on labor markets can serve as a first indication of what effects one might expect from internal migration. For example, well-known studies (e.g., Card 1990) looked at the impact of exogenous regional migration shocks, such as the 1980 Mariel boatlift, and found that migration had little impact on native wages. Critics argued that a possible cause for the absence of any observed effect of migration on natives is that natives might move to other local labor markets in response to an influx of migrants, thus masking the impact of migration on wages and employment. While some studies (e.g., Aydemir and Borjas 2007) use national data to overcome this problem and find a negative effect of migration on wages, Aydemir and Borjas (2011, p. 71) note that "the national labour market approach may find itself with as many different types of results as the spatial cor-

[8] More particularly, the seasonal migration from the northeast of Thailand, facilitated by wide networks of friends and relatives, has continued on a large scale (IOM 2008). This form of migration represents the main source of remittances for out-migration regions. However, there has been a slowdown in seasonal migration during the nineties because agricultural workers who migrate to urban areas for temporary employment tend to stay year-round (Chalamwong 1998).

relation approach that it conceptually and empirically attempted to replace."[9] An alternative explanation for the absence of important effects on wages and employment prospects for natives from an increase in migration is that native and migrant workers may be imperfect substitutes (Manacorda et al. 2006; Peri 2011; Ottaviano and Peri 2012). In particular, Manacorda et al. (2006) suggest, using data from the United Kingdom, that while migrants and natives are imperfect substitutes, migrants are close substitutes for other migrants, so that an increase in the stock of migrants lowers the wages of existing migrants but has little impact on natives. Arguably, however, internal migrants will be closer substitutes for native workers than international migrants so that these effects are less likely to be as important for interprovincial migration within Thailand. Card (2009) concludes that natives and migrants are perfect substitutes for high school dropouts but imperfect substitutes within higher-skilled groups. This conclusion is consistent with the results we present below, where we find labor market effects for low-skilled workers only.[10]

The empirical literature on the effect of internal migration on local labor markets in developing countries[11] tends to show that an increase in inward migration has negative effects on natives, but there is substantial heterogeneity in the results in terms of who is affected and whether the effect is on wages or employment probability. It may be that poor infrastructure, as suggested by Strobl and Valfort (2015), or other institutional barriers in developing countries restrict capital mobility or firm entry and exit and make the effects of migration on natives more negative. In this regard, Kleemens and Magruder (2014) use weather shocks to model internal migration in Indonesia and find effects on wages when migration is instrumented but no effects for ordinary least squares (OLS) estimates. These statistically significant effects are concentrated on low-skilled natives.[12] Strobl and Valfort (2015) use variation in the weather to model net internal migration in Uganda and find that migration

[9] Some examples of studies that have examined this question with mixed results are Bonin (2005), who reports a very weak impact of supply shifts on wages in Germany. Bohn and Sanders (2007) find a weak wage effect on the Canadian labor market. Aydemir and Borjas (2007) use data from Canada and Mexico and find a strong negative relationship between wages and supply shifts induced by immigration, while Mishra (2007) studies the Mexican labor market and finds a significant positive effect of emigration and wages in Mexico.

[10] In a recent reappraisal of the impact of the Mariel boatlift, Borjas (2015) presents evidence that there are indeed substantial negative wage effects on native high school dropouts from this large influx of largely low-skilled Cuban migrants into Miami in 1980.

[11] There is also a small literature on internal migration in developed countries. See, e.g., Berker (2011), Ham, Li, and Reagan (2011), and Kennan and Walker (2011).

[12] Kleemens and Magruder (2014) also look at the difference between formal and informal workers, where informal workers are not constrained by the minimum wage.

reduces employment, especially when road networks are poor. Maystadt et al. (2014) examine Nepal, where the range of push and pull factors used to model migration inflows and outflows across regions includes weather but also historical migration trends and measures of civil unrest and of environmental degradation, and they show that inward migration leads to lower wages for formal sector natives and a loss of employment and rise in unemployment for lower-skilled natives. Dillon, Mueller, and Salau (2011) provide evidence that internal migration in Nigeria has an insurance element in that it increases with the risk of adverse weather events. Analyzing interprovincial migration and inequality during Vietnam's transition, Phan and Coxhead (2010) find that the impact of migration on inequality can be either negative or positive, while Beals, Levy, and Moses (1967) study the migration phenomenon in Ghana and show that income differentials drive migration and that regions of large population are relatively more attractive. Sahota (1968) finds that internal migration in Brazil is highly responsive to earning differentials and inversely related to distance. More generally, economic costs and returns dominate the behavior of migrants. In a paper that is related to the analysis here, Yang (2004) studies the link between migration and cross-province inequality in Thailand and finds a significant effect of migration on income inequality. More particularly, she reports that a 1% increase in the mean fraction of outmigrants to Bangkok entails a 0.058 reduction in the average ratio of Bangkok's income to all other provinces.[13]

B. Literature on Hours Worked and Wages

Lundberg (1985), using Granger causality tests, rejects that wages of low-income married males are exogenous to hours and concludes that hours and wages respond positively to each other, although the effect of hours on wages is small. Biddle and Zarkin (1989) estimate a simultaneous model of wages and hours for males and find that wage rates increase up to a certain point, at which point they begin to decrease. In contrast, the taxation–labor supply literature argues that the hourly gross wage is independent of hours whereas the net wage is decreasing in hours (Rosen 1976; Burtless and Hausman 1978; Arrufat and Zabalza 1986). When examining most labor markets and their various institutional features, Vella (1993) explains the negative relationship between weekly hours worked and the gross hourly wage rate by the fact that employers and employees avoid taxation by substituting wages with nontaxable benefits as the total weekly wage increases.

[13] Vanwey (2003) analyzes the role of land ownership in rural temporary migration in Thailand.

C. Using Distance as a Determinant of Migrant Destination Choice

Taking account of distance in measuring how such weather variation will affect migration between provinces is grounded in the arguments that distance constitutes an important determinant of the location choice of migrants. As a matter of fact, Bryant and Rukumnuaykit (2007) used distance from the Myanmar border to instrument migration from Myanmar to Thailand and find that migration reduces wages of Thai workers.[14] Using the constructed instruments for Thailand, we find that inward migration has a substantial negative impact on weekly wages of low-skilled male natives, but this results from a reduction in weekly hours rather than the hourly wage rate.

III. Data and Sample Selection

We use data on males from the Thai Labour Force Survey between 1991 and 2000. The survey is conducted several times a year, with increasing frequency in more recent years. We have access to the February and August surveys for each year. The survey is a large cross section where, for example, the February 2000 survey interviews more than 164,000 individuals, providing a wide variety of information on location, employment status, job characteristics, and income as well as demographic characteristics. One may want to note that August is in the middle of the wet season in Thailand, while February is at the beginning of the dry season. In this regard, Chamratrithirong et al. (1995, p. 14) note that the "highest levels of seasonal migration occur during the dry season months of February through May when many farmers start looking for temporary work to tide them over until the next planting season." On the other hand, one might expect the demand for agricultural workers to be higher in the August round, so that there may be differences in returns to migration across seasons that reflect both supply and demand factors.

There are 72 provinces in Thailand, as shown in figure 1. In addition to providing the name of the province where they live, individuals answer the following question: "How long have you been living regularly in this village/municipality?" Respondents can choose from the following answers: less than 1 year, 1 year, 2 years, up to 9 years, and more than 9 years. We calculate the number of recent arrivals as those who answer less than or equal to 1 year. This represents 52.4% of total movers to new provinces.[15] We use this subsample of movers to compute the inflow and outflow rates. We then define the province of origin and the destination province of all movers as people

[14] See also Sjaastad (1962), Sahota (1968), and Schwartz (1973).

[15] Note that the category of movers within provinces represents 29% of all movers and that 49.4% of the sample of movers from this category moved 1 year ago at most.

Figure 1. Thai provinces.

are asked, "Which is the previous province of your residence before moving here?" The survey then asks for the reason of migration. In this regard, among recently moved people, some 35.71% were looking for a job or occupation, 7.62% of respondents migrate for further study, 22.75% follow their family, 28.53% report coming back to their former residence, and 0.22% of migrants state moving from one province to another in order to be nursed. Concerning the province of destination, Bangkok accounts for the largest proportion of arrivals, with 7.2% of total recent migrants.[16] We construct a sample of nonmigrants residing in the 72 Thai provinces, where we exclude people who moved within the same province. Table A3 (tables A1–A6 are available online) presents the share of incumbents and migrants by region, skill group, season, period, and residence area type.

For the regression analysis, we reduce the sample to men ages 15–64 years who were not attending school at the moment of the survey and who work 95 hours or less.[17] There are three categories of workers: employees, self-employed in business, and self-employed in agriculture. These are treated as mutually exclusive in the data in that an employee is not asked the questions on self-employment while a worker self-employed in business is not asked the employee questions. For employees, the earnings questions ask workers if they are paid hourly, daily, weekly, or monthly and what the rate of pay is for the relevant category. Table A1 gives summary statistics and shows that 99% of employees are paid either daily or monthly. Most waged workers at the low skill end of the labor market are paid daily, where we define low skill as those with less than secondary education. We drop employees in government or public service workers as well as employees who are in unpaid jobs. After controlling for missing values, the sample used in all the wage and hours regressions below consists of 194,410 for observations. Low-skilled workers account for 130,049 of these.[18]

Self-employed workers in either agriculture or business are asked the net monthly profit from the enterprise in the previous month and also the number of household members who work in the enterprise. Apart from the difficulty in assessing net profit, which is likely to contain substantial measurement error, we do not have any way of knowing how the net profit is distributed across household members. We construct the individual monthly wage by dividing the monthly net profit by the number of household members involved in the business; that is, we assume that profit is distributed equally across workers in the household. This is also likely to introduce substantial measurement error. We use this to construct a weekly wage from self-employment in agriculture or business. Hours worked data are available at the individual level, and we use this to construct an individual hourly wage. We should stress that the hours worked data for self-employed workers are collected in the same way as for employees and are not subject to the same measurement problems as self-employed wages/profits.

[16] The second-best destination province is Udon Thani, with 4.26% of total recent migrants.
[17] We focus on males to avoid the sample selection issues associated with females who have lower participation rates.
[18] High-skilled persons are limited to those with an educational level beyond the secondary level.

Tables A1 and A2 provide summary statistics separately for the subsamples of employees, self-employed in agriculture, and self-employed in business. As can be seen, weekly wages are higher for natives than for migrant employees. At the same time, the former work marginally less hours per week. If one examines remuneration for the self-employed, one finds that native self-employed in business earn the highest while migrant agricultural self-employed earn the lowest—in fact, multiple times less than the former. Working hours differ little between the various self-employed, except for native self-employed in agriculture, who work a few hours less than the other groups.

IV. Econometric Analysis

A. Construction of Instruments

In order to construct instruments for migration, we follow the methodology proposed by Boustan et al. (2010), which consists of predicting the total outflow (inflow) from a province induced by weather shocks and then decomposing this outflow (inflow) into destination province by estimating the role of geographic distances in determining interprovincial flows. We then use both weather and distance to construct the predicted inflow (outflow). More specifically, for the case of migration inflow, this first involves regressing total outflow rates of each province on a set of climate determinants:

$$Orate_{i,t-1\rightarrow t} = \alpha + \delta' Z_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $Orate_{i,t-1\rightarrow t}$ is the outflow rate from source province i over time period $t-1$ to t, Z is a vector of climate-specific indicators, and ε is an error term. Using the estimated coefficients from equation (1), we find that the predicted flow of migrants leaving each region i, $\tilde{O}_{i,t-1\rightarrow t}$, is then just equal to the predicted outflow rate, $\bar{O}rate_{i,t-1\rightarrow t}$, times the population at $t-1$:

$$\tilde{O}_{i,t-1\rightarrow t} = \bar{O}rate_{i,t-1\rightarrow t} \times \text{Population}_{i,t-1}. \quad (2)$$

One then separately for each sending area i regresses the actual set of destination-specific outflow rates to each destination province j on their relative distances and its squared and cubic value:[19]

$$Orate_{ij,t-1\rightarrow t} = \alpha_i + \theta_i \text{Distance}_{ij} + \theta_i \text{Distance}_{ij}^2 + \theta_i \text{Distance}_{ij}^3 + \mu_{i,t}. \quad (3)$$

[19] One should note that Boustan et al. (2010) regress these rates only on distance and its squared value. For the case of Thailand we found that including its cubic value substantially increased the specifications fit.

The instrument for in-migration to province j, $\bar{\bar{I}}_{j,t-1\to t}$, is then just the sum of the predicted number of migrants over all areas ($i \neq j$), $\bar{O}rate_{ij,t-1\to t}$, expected to settle in province j:

$$\bar{\bar{I}}_{j,t-1\to t} = \sum_{i=1,\ldots,n\,(i\neq j)} \tilde{O}_{i,t-1\to t} \times \bar{O}rate_{ij,t-1\to t}. \quad (4)$$

One can then in a similar manner construct predicted outflow from area j by predicting the in-migration rates to each receiving area i using climatic determinants, using these rates to predict the number of inflowing migrants into i, and then constructing predicted outflow migrants by multiplying this figure by the distance and its nonlinear terms estimated inflowing rates between provinces i and j ($i \neq j$).

In order to estimate equation (1) as well as its analogous specifications for the in-migration, we use for vector Z a number of measures that capture weather conditions in a province. In order to identify periods of extreme wetness and dryness in provinces, we first calculated the local standardized precipitation index (SPI)—which has been argued to be particularly good at capturing the cumulative effect of high and low patterns of rainfall over time in a chosen locality—from the mean monthly precipitation values within our provinces, as calculated from the Intergovernmental Panel on Climate Change (IPCC) data set.[20] Following McKee et al. (1993), we then define a monthly extremely dry (wet) event as starting when the SPI reaches an intensity of −2.0 (2.0) or less (more) and as ending once the index become positive (negative) again. For each time period we then calculate the number of months of extreme dryness (wetness). The corresponding constructed variables are DRY and WET, respectively. To capture the effect of temperature, in particular with respect to its importance for agriculture, we construct a measure of reference evapotranspiration (ET) to represent the evaporative demand of the air within a basin. Following Hargreaves and Samani (1985), evapotranspiration is calculated as

$$\text{ET} = 0.0023\left(T_{\text{avg}} + 17.8\right)\left(T_{\max} - T_{\min}\right)0.5R_a, \quad (5)$$

[20] The calculation of the SPI is based on modeling the probability distribution of precipitation as derived from long-term records by fitting these to a gamma distribution via maximum likelihood. An important component in this regard is the chosen timescale. Since we are interested in cropland productivity, and soil moisture conditions are known to respond to precipitation anomalies over a relatively short time period, we use a 12-month scale. See http://www.drought.unl.edu/whatis/indices.htm.

where T_{avg}, T_{max}, and T_{min} are mean, maximum, and minimum temperature, respectively, and R_a is the extraterrestrial radiation calculated following Allen et al. (1998). Since the effects of rainfall shortages and abundance on local agricultural are likely to some extent to depend on the local evaporative demand, we also allow for interactions between ET and WET and DRY. To construct all these climatic factors at the provincial level, we resort to information from the IPCC climatic data set, which provides monthly precipitation and temperature measures across the globe at the 0.5° level over the entire twentieth century. We use these to calculate time-varying averages within provinces.

The results of estimating equation (1) for the annual provincial out- and inmigration rates—controlling for provincial specific fixed effects and provincial common time specific factors—are given in table 1, panel A. We calculate Driscoll and Kraay (1998) standard errors corrected for spatial and temporal correlation throughout. As can be seen, for both inflow and outflow rates, the set of climatic variables are almost all significant, producing highly significant F-tests of joint significance. Examining the individual factors, one finds that for the precipitation-related factors the signs meet a priori expectations. More specifically, one finds that extremely dry as well as extremely wet weather, indicative of drought and flood-like conditions, respectively, act to increase overall outflow from regions. In terms of economic significance, the estimated coefficients imply that 1 month of dry (wet) weather would increase the outflow rate by 7.9 (10.5) percentage points. Moreover, the negative impact of rainfall shortage is further exacerbated by a high evapotranspirative demand of the air. Somewhat surprisingly, the direct effect of evapotranspiration is to reduce outflow from a province, although in absolute terms this impact is small. For the inflow rate, one finds that extremely wet periods tend to reduce the inflow rate, while droughts have no significant effect. Using the estimated coefficients indicates that 1 month of extremely wet weather would decrease the inflow rate by 0.7 percentage points. Furthermore, we find that a high evapotranspirative demand of the air tends to reduce the effect of the latter. Surprisingly, one finds that this demand on its own acts to increase person flowing to the province, although again not substantially so. To construct the predicted inward and outward migration rates by subgroup, we proceeded in a similar manner as for the overall sample, except restricting construction via equations (1)–(4) to the subsample in question. We report the estimation for equation (1) for the outflow and inflow rates in tables 1, panels B and C, respectively. As can be seen, for the outflow rate all climatic variables are significant, where the signs are in congruence with the overall sample. Unsurprisingly, the joint F-tests attest to their power as predictive factors. For the inflow rates, the majority

TABLE 1
EFFECT OF WEATHER ON MIGRANT FLOWS, OUTFLOW RATES, AND INFLOW RATES

	A. Effect on Migrant Flows		
	Out Rate	In Rate	
DRY	.00266*	−2.45E−05	
	(.00130)	(.000964)	
WET	.00352*	−.00358**	
	(.00135)	(.000701)	
EVAPO	−.000222*	.000710**	
	(8.90E−05)	(.000192)	
EVAPO × WET	3.04E−05	−5.95E−05**	
	(1.55E−05)	(1.16E−05)	
EVAPO × DRY	3.36E−05*	−1.34E−05	
	(1.56E−05)	(6.74E−06)	
Observations	1,440	1,440	
Number of groups	72	72	
F-test	4.963	8.616	
	B. Effect on Outflow Rates		
	(1)	(2)	(3)
DRY	.00142*	.00166*	.00120
	(.000625)	(.000648)	(.000618)
WET	.00235**	.00231**	.00238**
	(.000709)	(.000692)	(.000736)
EVAPO	−.000227**	−.000262**	−.000197**
	(7.61E−05)	(8.85E−05)	(6.81E−05)
EVAPO × WET	2.75E−05**	2.54E−05**	2.95E−05**
	(7.25E−06)	(7.64E−06)	(7.35E−06)
EVAPO × DRY	1.88E−05*	2.14E−05*	1.65E−05*
	(7.68E−06)	(9.34E−06)	(6.40E−06)
Sample	Males	Low Skilled	High Skilled
Observations	1,440	1,440	1,440
Provinces	72	72	72
F-test	9.028	8.172	9.926
	C. Effect on Inflow Rates		
	(1)	(2)	(3)
DRY	−.000417**	−.000562**	−.000375**
	(.000153)	(.000129)	(.000129)
WET	−.000891*	−.000797*	−.000764**
	(.000366)*	(.000325)	(.000266)
EVAPO	.000636**	.000613**	.000439**
	(.000182)	(.000163)	(.000160)
EVAPO × WET	−8.68E−06	−5.18E−06	−9.63E−06
	(6.42E−06)	(5.34E−06)	(4.97E−06)
EVAPO × DRY	−9.25E−06	−9.87E−06	−9.74E−06
	(1.10E−05)	(7.63E−06)	(6.74E−06)
Sample	Males	Low Skilled	High Skilled
Observations	1,440	1,440	1,440
Provinces	72	72	72
F-test	18.15	31.16	8.963

Note. Driscoll and Kraay (1998) standard errors corrected for spatial and autocorrelation in parentheses. Year and biannual dummies included but not reported. *F*-test is test of joint significance of the climatic variables.
* Significance at 5% level.
** Significance at 1% level.

of coefficients are significant and similar to those from the overall sample. Similarly, the *F*-test statistics provide evidence of their predictive power.

In terms of estimating equation (3), since this involves estimating different specifications for each province, we provide only a brief outline of the results. One may want to note first that since our distance measures do not vary over time, our estimated specification in equation (3) does not control for province specific effects but does include a set of time dummies to control for common region time specific factors determining the migration flows. We used Driscoll and Kraay (1998) standard errors corrected for spatial correlation, as we did for equation (1). For each province-specific regression, after estimating the parameters on distance we conducted an *F*-test of the null hypothesis that these were jointly 0. In the case of out-migration rates for only four provinces while in the case of in-migration rates for only six could the null hypothesis not be rejected. As with the overall sample, the *F*-test of the distance variables suggested strong predictive power in almost all cases for the estimation of (3) for subgroups. Finally, we depict the average relationship between distance and inflow and outflow rates in figures 2 and 3, respectively. As can be seen, the shape in general suggests a nonlinear decreasing relationship between the rates and distance, where the marginal change is high at very short and very long distances.

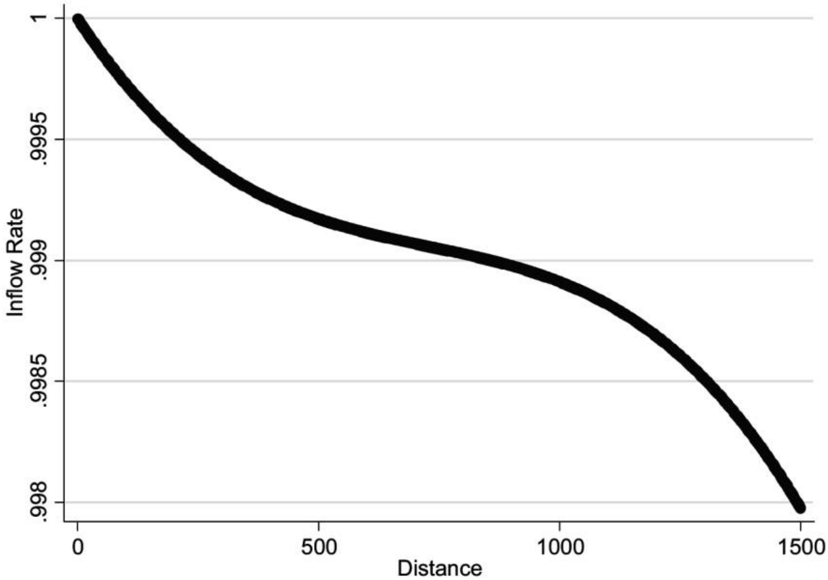

Figure 2. Average relationship between distance and inflow rate.

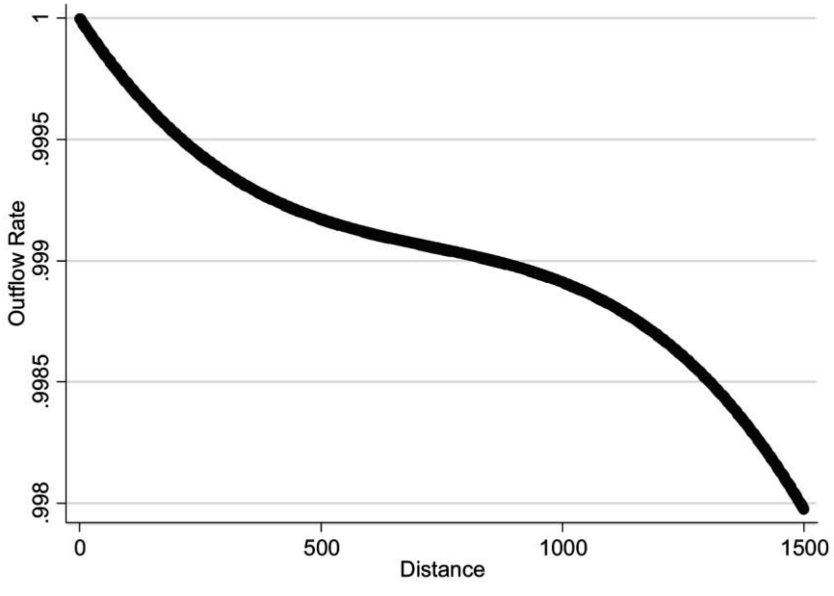

Figure 3. Average relationship between distance and outflow rate.

In table 2 we report the results from the first-stage regression of our instrumental variables specifications, where we use predicted migration rates constructed as outlined above to predict actual net migration rates. Table 2 shows the results for men by skill. As can be seen and indicated by the *F*-test on the instruments, the predicted inflow rate variables significantly predict an increase in actual net migration, whereas predicted out-migration rate acts to decrease net migration. Using bootstrapped standard errors and the corresponding Wald tests shows similar results, although standard errors are somewhat larger. A notable feature of table 2 is that, if anything, migration flows are a little larger in the high-skilled group.

Table 3 provides average actual and instrumented inflow and outflow rates by broad region and season for the subset of the population who are in employment. Looking at the actual flows one can see that while there is considerable variation across region, flows from Bangkok are the highest over our sample period. Instrumented flows predicted by weather changes are much smaller than the actual, where predicted inflows and outflows are symmetric, as we would expect for migration associated with random shocks across provinces. One may also want to note that the instrumented flows are much smaller in Bangkok than in other regions. We use the binary variable—which asks participants if they live in a municipal area as a proxy for urban or rural area—and provide in table 4 the average flows decomposed by this urban-rural proxy. Ac-

TABLE 2
RELATIONSHIP BETWEEN PREDICTED AND ACTUAL MIGRATION FOR MALES BY SKILL

	Total	Low Skilled	High Skilled
WLS regression:			
Predicted in-migration rate	5.332**	3.007**	3.262**
	(2.592)	(1.300)	(1.387)
Predicted out-migration rate	−9.537***	−4.101***	−5.539***
	(2.302)	(1.128)	(1.219)
F-statistic	15.1	16.1	12.4
Bootstrapped procedure:			
Predicted in-migration rate	5.576*	3.103**	3.491**
	(3.088)	(1.424)	(1.549)
Predicted out-migration rate	−9.591***	−4.168***	−5.490***
	(2.756)	(1.243)	(1.398)
Wald's statistic	2,057	1,704	3,535

Note. Regressions are estimated using individual data from the Thai Labour Force Survey from 1991 to 2000. Standard errors are clustered by provinces and waves. Dummies for salary period of payment (hourly, daily, weekly, and monthly) are introduced. For wage regressions, we introduce the number of weekly working hours and its squared term. We include both the high-skilled and the low-skilled net instrumented migration rate for each of the six subsamples shown above.
* Significance at 10% level.
** Significance at 5% level.
*** Significance at 1% level.

cordingly, actual outflows are a little higher in municipal (urban) areas compared with nonmunicipal ones, but there is no difference in inflow rates. Similarly, there is no noticeable difference in the predicted inflow or outflow rates by urban-rural status.

Tables 3 and 4 also provide the flows across the high and low season and indicate that there is no noticeable difference in inflow or outflow rates across seasons. In general the tables suggest substantial flows of recent migrants and

TABLE 3
ACTUAL AND INSTRUMENTED INFLOW AND OUTFLOW RATES (%) BY SEASON

	Actual		Instrumented	
Region	Outflow	Inflow	Outflow	Inflow
Low season:				
Bangkok	13.60	5.56	.03	.02
Central	2.98	4.70	.18	.15
North	3.23	3.83	.15	.16
Northeast	3.63	5.18	.11	.12
South	2.98	2.52	.12	.11
High season:				
Bangkok	15.39	4.73	.04	.02
Central	3.14	4.52	.20	.15
North	3.27	4.21	.16	.16
Northeast	3.63	6.01	.12	.12
South	2.98	2.50	.13	.11

TABLE 4
ACTUAL AND INSTRUMENTED INFLOW AND OUTFLOW RATES (%) BY MUNICIPAL

	Actual		Instrumented	
Region	Outflow	Inflow	Outflow	Inflow
Low skilled:				
Nonmunicipal	2.69	3.64	.30	.29
Municipal	4.77	3.70	.24	.22
High skilled:				
Nonmunicipal	2.53	3.47	.29	.28
Municipal	4.67	3.61	.24	.21
Low season:				
Nonmunicipal	3.23	4.26	.14	.14
Municipal	5.34	4.52	.12	.11
High season:				
Nonmunicipal	3.23	4.56	.15	.14
Municipal	5.75	4.45	.12	.11

that these flow across most regions and are not dominated by seasonal or urban/rural migration. While our prior would have been that in particular migration flows generated by weather shocks would generate larger rural urban flows, in particular it may be that weather conditions also have implications for labor demand in urban sectors, such as tourism or construction. Table A1 summarizes the distribution of workers across broad occupation groups by migrant status. The results are consistent with the finding that migration flows are not especially dominated by seasonal urban-rural migration. The occupation category farmer/fisherman/hunter accounts for about 12.6% of natives but only 8.8% of recent migrants, and there is a similar breakdown for the industry category agriculture, forestry, and fishing. While migrants account for 11% of employees, they account for only 5% of self-employed workers in agriculture or business (tables A1, A2). In other words, it appears that most migrants are working as employees in nonagricultural jobs and are less likely than natives to be in these jobs.

Another notable feature from tables 3 and 4 is that there is no noticeable difference in inflow and outflow rates from weather shocks by skill level. In this regard, one might have expected that weather-induced migration would be higher for low-skilled workers, given that their employment is likely to be in low-skilled manual occupations that might be more affected by the weather. Of course, on the other hand, higher-skilled workers may be more mobile, where there is often a selection effect in that higher-skill workers are more likely to move. However, one should bear in mind that the cutoff for high skill is not very high, so that there may be substantial numbers with more than an elementary education in manual jobs who are categorized as high skill but whose skill level is not that high. We do conduct some robustness tests with alternative skill measures in our regression analysis below, but as we move up the skill distribution, sample size falls substantially in the high-skilled group. Given this, arguably our results are more convincing for the low-skilled group because we can identify a large sample of workers with very low educational attainment while attainment in our high-skilled group is more dispersed.

B. Effect of Net Migration on the Local Labor Market

We next examine the impact of net inward migration on the log weekly wage, weekly hours, and log hourly wage for males of working age (15–64 years), controlling for individual characteristics. In particular, when we look at the impact of migration on the log wage, we control for age and age squared, marital status (four dummies indicating single, married, widowed, or divorced status), a dummy indicating whether the worker lives in a municipal area, and a set of 12 educational indicator dummies and for weekly hours, hours worked, and hours squared when the dependent variable is the log of the weekly wage. For our sample of private sector employees we also include 10 occupation dummies, 10 industry dummies, seven firm-size dummies, and dummies indicating whether the worker is paid hourly, daily, weekly, or monthly. Additionally, we include average age and the fraction of workers with no education at the province level as well as province- and time-specific effects in all specifications for employees and self-employed in business or agriculture.

The results on the estimated coefficient on the net inward migration rate for the log weekly wage and weekly working hours are reported in tables 6–9. In table 6 in the first column, the coefficient of −0.059 on log weekly wages in the OLS results for all males indicates that a 10 percentage point increase in the net migration rate (which means the population increases by 10% as a result of net migration) is associated with a decrease in male wages of about 0.6%. A clear worry here is that, as noted earlier, we might expect migration inflows to depend on local economic conditions, which also affect the wage level or level of hours worked. For example, in terms of a simple competitive model, an increase in labor demand in any province would be expected to increase inward migration and labor supply but also wages in that province. On the other hand, inward migration and labor supply in any province will also increase because of changes in demand or supply conditions in other provinces and thus lead to a fall in wages. In other words, the theoretical predictions from regressing uninstrumented migration flows—which are a mixture of supply and demand effects—on wages are unclear. As a matter of fact, the results from the instrumental variables regressions discussed below confirm that this worry is legitimate. More precisely, taking account of the endogeneity of migration, one finds that the weekly wage decreases by 3.5% when migration increases the population by 10 percentage points.

In examining the effect of migration on hours worked, we report the coefficients on hours from the OLS and instrumental variables regressions on hours worked. We find that while OLS results produce a small insignificant coefficient, the instrumental variables model suggests that a 10 percentage point increase in population due to migration lowers weekly hours by about 1.07 hours. We also report the percentage change in hours implied by the instrumental variables estimates in the regression tables.[21] For these instrumental variables estimates, the estimated coefficient implies a percentage reduction of just over 2% in hours from an increase in population of 10%, although we note that the underlying coefficient is only statistically significant at the 10% level. We supplement these results with the results from table 10, which reports the effect of migration on the probability that a worker wishes to work longer hours in the previous week using a linear probability model. In this regard, if inward migration were associated with an increase in the probability that the worker wishes to work longer hours, this could be viewed as being consistent with the evidence in table 6 that migration reduced hours worked as well as suggesting that this reduction in hours was involuntary. We see that for both the OLS and instrumental variables specifications, a 10% increase in population increases the probability that an incumbent wishes to work longer by 0.8% and 2.4%, respectively, although the larger coefficient for the instrumented specification is significant only at the 10% level.

Table 6 also provides results by high- and low-skilled group. Here we find that there are no statistically significant effects for the high-skilled group apart from a marginally significant fall in the hourly wage in the OLS results. In contrast to this, we will see throughout the remainder of the results that there are clear effects for low-skilled migrants. In this respect, as noted earlier, the predicted migration flows are very similar across skill groups, suggesting that weather-induced migration is not primarily low skilled. As a matter of fact, the literature on international migration often shows that migrants tend to be more highly educated in a given occupation compared with natives so that there is a disproportionately high share of high-skilled migrants in low-skilled occupations (see, e.g., Walsh 2013).[22] If this were true for Thailand, then one might observe high-skilled migrant flows where these migrants compete for low-

[21] The regression coefficients on hours report the change in hours from a 10 percentage point increase in the population. To convert this into an elasticity evaluated at the average level of hours, we divide the coefficient by the average hours of the sample.
[22] See, e.g., Walsh (2013).

skilled jobs at their destination and that affect only the wage and hours outcomes in low-skilled sectors. To further examine this, table 5 depicts the share of high-skilled workers in each occupation category by migrant status, but there appears to be no evidence of this effect. Rather, the share of high skill across occupation groups is broadly similar and not noticeably higher for migrants in low-skilled occupations. Perhaps this is because the differences between internal and international migrants are small so that migrants can find jobs in line with their skill. In terms of explaining why it is that the effects we find in table 6 and indeed for most of the paper are more pronounced for low-skilled workers, it may be that, given that the summary statistics in table 5 indicate that high-skilled and low-skilled migrants are not typically competing for the same types of jobs, the nature of the technology may different for high-skilled employees. For example, one would expect on-the-job training and job-specific skills to be more important in high-skilled jobs so that wages and hours are set in longer-term contracts so that the responses to short-term labor supply shocks are smaller. Also, as we noted earlier and discuss in more detail below, the absence of statistically significant effects for high skill may partly reflect the possibility that our categorization of high skill implies that the high-skilled sample will possibly include substantial heterogeneity in skill levels.

The results for low-skilled workers in table 6 show that the OLS coefficients are all statistically insignificant while the instrumented regressions predict that a 10% increase in population will lower the weekly wage by just under 6% and lower hours by 4%. There is no statistically significant effect on the hourly wage. Given that these changes in weekly hours and earnings suggest a rise in hourly wages of less than 2%, arguably this is not too surprising. One may also want to note that the difference in the effect on weekly wages and hours between skill levels is not statistically significant.

TABLE 5
SHARE OF HIGH SKILL BY OCCUPATION AND MIGRANT STATUS

	Occupation	Incumbents	Migrants
0	Professional	.951499	.932091
1	Administrative/management officer	.594614	.697959
2	Financial/fiscal and accounting clerks	.796385	.829268
3	Wholesale/retail trader/owner	.402399	.470088
4	Farmer/fisherman/hunter	.102532	.127994
5	Miner/quarry worker	.175595	.122449
6	Transportation	.268199	.342033
7	Cotton spinner/weaver/knitter	.294560	.316324
8	Type cutter/printer/bookbinder	.209808	.239597
9	Services/sports	.350680	.387570

TABLE 6
EFFECTS OF NET INFLOW RATE ON EMPLOYEES: CHECKING FOR NIGHT-LIGHTS

	Specification 1			Specification 2	Specification 3
	Males	High Skilled	Low Skilled	Low Skilled	Low Skilled
OLS:					
Log weekly wage	−.059**	−.043	−.043	−.040	−.053*
	(.027)	(.030)	(.032)	(.031)	(.031)
R^2	.593	.635	.460	.460	.478
IV:					
Log weekly wage	**−.348****	−.186	**−.578****	−.470*	**−.508****
	(.140)	(.134)	(.257)	(.249)	(.216)
R^2	.593	.635	.458	.459	.476
OLS:					
Log hourly wage	−.084**	−.094*	−.068	−.065	−.073*
	(.042)	(.057)	(.044)	(.044)	(.042)
R^2	.589	.639	.408	.408	.433
IV:					
Log hourly wage	−.217	−.205	−.356	−.256	−.304
	(.149)	(.155)	(.245)	(.238)	(.206)
R^2	.589	.639	.408	.408	.433
OLS:					
Weekly hours	1.305	2.201	1.276	1.256	.700
	(2.144)	(2.276)	(2.622)	(2.631)	(2.447)
R^2	.124	.150	.104	.104	.104
IV:					
Weekly hours	**−10.67***	1.091	**−20.65****	**−20.60****	**−19.40****
	(5.916)	(4.288)	(10.02)	(10.23)	(8.947)
IV:					
Elasticity weekly hours	−.209	.022	−.396	−.395	−.371
R^2	.122	.150	.099	.104	.100
Observations	182,085	60,245	121,840	121,840	130,049

Note. Specification 1 includes the night-lights variable. Specification 2 excludes the night-lights variable but uses the same sample for low-skilled males as specification 1. Specification 3 excludes the night-lights variable for the low-skilled males and includes the extra waves. Robust standard errors are in parentheses. We report coefficient estimates in bold if they are significant on the basis of Anderson-Rubin (Anderson and Rubin 1949) robust 95% confidence intervals. IV, instrumental variables; OLS, ordinary least squares.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

One aspect that could potentially undermine our instrumental variables strategy is that weather shocks that affect agricultural productivity may affect the supply of agricultural goods and demand for industrial goods and hence affect wages and employment in areas not directly impacted by the shocks. To take account of this, we follow Strobl and Valfort (2015) and use satellite-derived night-light imagery as a proxy for local economic conditions.[23] The re-

[23] Night-light intensity is measured from the satellite-derived measures, as taken from the Defense Meteorological Satellite Program satellites, which provide normalized light intensity at night at the approximately 1-square-kilometer-grid cell level across the globe. Since the public data are annual, we linearly interpolate between-year values to obtain semiannual estimates. One should note that

sults of which are shown in specification 3, where specification 2 does not control for night-lights but uses the same subsample for which this variable is available. As can be seen, the results are very similar for all specifications; that is, including a control for provincial demand does not seem to substantially alter the results. Excluding the two waves of data where night-lights are not available does make the coefficients on net migration less precise, but this may be in part simply because, as we will show below, the effect is more precisely estimated in the period before the 1997 financial crisis.

Our definition of skill is arguably a somewhat arbitrary cutoff in that we define high skill as individuals with secondary education or higher. While less than secondary education is arguably a reasonable categorization of low skill, as we noted earlier there is likely to be substantial variation in skill levels for workers categorized as high skill by this definition. To test whether changing this cutoff makes much difference, we try alternative definitions of skill in table 7. In this regard, specification 1 shows results where high skill is defined to be greater than lower elementary, while specification 2 employs the same definition except that it excludes the night-lights variable and thus uses all waves of data. We see that the results are broadly similar to what we saw in table 6. There are some marginally significant very small negative effects for high skill males in the OLS specification, but these are not statistically significant in the instrumented regressions. For the low-skilled sample, the instrumented regressions predict a fall in weekly wages of 8.1%, which is driven by a reduction in hours of 5.2% when population increases by 10%; interestingly, this estimate of the elasticity of weekly earnings is larger than the estimate of 5.8% for the broader definition of low skill contained in table 6. Specification 3 looks at a narrower definition of high skill by limiting it to those with upper secondary education or more. As can be seen, there are no statistically significant results using this alternative definition but the sample size is much smaller for high skill workers using this categorisation.[24]

In table 8 we investigate the role of the Asian financial crisis, which began in Thailand in 1997 and led to a severe downturn. To look at the effects of this negative aggregate demand shock we split the sample into waves before and after February 1997. This seems to make a substantial difference to the results. While the OLS results suggest a statistically significant fall of about half an

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the use of night-light imagery has now been used in a number of studies to proxy local economic activity; see, for instance, Chen and Nordhaus (2011) and Henderson, Storeygard, and Weil (2011).

[24] We should note that the underlying migration flows used in these regressions are based on the original skill definition. The alternative definition of skill is only used to divide the sample used in the regressions.

TABLE 7
EFFECTS OF NET INFLOW RATE ON EMPLOYEES: ALTERNATIVE MEASURES OF SKILLS

	Specification 1		Specification 2		Specification 3
	High Skilled	Low Skilled	High Skilled	Low Skilled	High Skilled
OLS:					
Log weekly wage	−.050*	−.035	−.079**	−.042	−.061
	(.029)	(.042)	(.032)	(.038)	(.039)
R^2	.640	.467	.645	.483	.638
IV:					
Log weekly wage	−.092	−.817**	−.104	−.727**	−.146
	(.127)	(.355)	(.113)	(.299)	(.134)
R^2	.640	.464	.645	.481	.638
OLS:					
Log hourly wage	−.094*	−.056	−.108**	−.061	−.082
	(.054)	(.047)	(.053)	(.044)	(.064)
R^2	.644	.404	.650	.428	.641
IV:					
Log hourly wage	−.032	−.543	−.024	−.463*	−.197
	(.149)	(.333)	(.134)	(.277)	(.169)
R^2	.644	.403	.650	.427	.641
OLS:					
Weekly hours	2.315	.241	1.288	.018	.649
	(2.381)	(2.522)	(2.367)	(2.288)	(1.910)
R^2	.138	.108	.141	.108	.168
IV:					
Weekly hours	−3.546	−27.32**	−5.010	−26.53**	2.574
	(5.015)	(12.54)	(4.574)	(11.24)	(4.012)
IV:					
Elasticity weekly hours	−.071	−.523	−.100	−.507	.054
R^2	.137	.101	.140	.100	.168
Observations	101,210	80,875	107,722	86,688	37,379

Note. Specification 1 includes the night-lights variable, and low skill is an education level of lower elementary or less. Specification 2 excludes the night-lights variable and uses all waves. In specification 3, high skill is an education level greater than upper secondary. Robust standard errors are in parentheses. IV, instrumental variables; OLS, ordinary least squares.
* $p < .1$.
** $p < .05$.
*** $p < .01$.

hour for employees across skill groups for a 10% increase in population, as with the earlier results the instrumented results suggest that the hours effect is concentrated in low-skilled employees who had a percentage fall in hours of about 2.3% for a 10% increase in population and a fall in weekly wage of about 3%. Broadly the effects are much stronger for the precrisis period than the postcrisis period. In this regard, the Thailand Migration Report (2011, p. 15) in its analysis of internal migration noted that the 2009 National Migration Survey reported that "73.9 per cent of rural migrants said that their most recent migration was to return home, an increase over the 66.4 per cent from who said this in 2008. This finding provides evidence that return migration is a common response in times of economic contraction." Thus, it is plausible in

TABLE 8

EFFECTS OF NET INFLOW RATE ON MALES: BEFORE VERSUS AFTER FINANCIAL CRISIS PERIOD

	Before					After				
	Employees	High Skilled	Low Skilled	Business	Agriculture	Employees	High Skilled	Low Skilled	Business	Agriculture
OLS:										
Log weekly wage	−.149***	−.150***	−.076	.303*	−.581	−.082**	−.009	−.091**	−.108	.240
	(.048)	(.053)	(.048)	(.171)	(.374)	(.037)	(.043)	(.039)	(.070)	(.159)
R^2	.594	.634	.469	.268	.450	.586	.638	.433	.224	.419
IV:										
Log weekly wage	−.287***	−.173*	−.388***	−.030	2.591**	−.796	−.347	−.327	.084	−.269
	(.086)	(.105)	(.136)	(.313)	(1.042)	(.704)	(.343)	(.341)	(.420)	(.449)
R^2	.594	.634	.469	.268	.447	.582	.637	.432	.224	.419
OLS:										
Log hourly wage	−.084	−.053	−.022	.427**	−.769*	−.147**	−.150	−.148**	−.154*	.187
	(.052)	(.060)	(.050)	(.186)	(.399)	(.075)	(.102)	(.071)	(.090)	(.194)
R^2	.593	.641	.426	.229	.491	.568	.638	.336	.181	.473
IV:										
Log hourly wage	−.188**	−.084	−.287**	.128	2.509**	−.413	−.855	−.148	.260	−.763
	(.091)	(.111)	(.139)	(.321)	(1.161)	(.494)	(.546)	(.336)	(.478)	(.628)
R^2	.593	.641	.426	.229	.488	.568	.635	.336	.181	.472
OLS:										
Weekly hours	−5.904***	−4.806***	−6.678***	−8.354***	12.95**	4.982	6.773*	5.187	3.781	2.328
	(1.160)	(1.204)	(1.678)	(2.372)	(5.831)	(3.712)	(3.733)	(4.591)	(3.062)	(2.774)
R^2	.128	.161	.097	.035	.270	.123	.152	.113	.052	.341
IV:										
Weekly hours	−9.085***	−4.021	−12.17***	−10.07**	15.43	−30.34	29.74	−19.01	−7.670	19.32*
	(2.564)	(2.552)	(4.181)	(4.957)	(17.29)	(37.70)	(19.30)	(22.43)	(9.762)	(10.65)
IV:										
Elasticity weekly hours	−.175	−.081	−.229	−.181	.295	−.608	.616	−.374	−.141	.391
R^2	.127	.161	.097	.035	.270	.098	.139	.105	.050	.340
Observations	122,378	38,480	83,898	108,540	110,398	72,032	25,881	46,151	75,175	72,012

Note. Regressions are estimated using individual data from the Thai Labour Force Survey from 1991 to 2000. Standard errors are clustered by provinces and waves. Dummies for salary period of payment (hourly, daily, weekly, and monthly) are introduced. For weekly wage regressions, we introduce the number of weekly working hours and its squared term. With the instrumental variable technique, we include the net instrumented migration rate specific for each subsample. IV, instrumental variables; OLS, ordinary least squares.

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

the Thai context that a substantial demand shock, as was the 1997 crisis, could lead to changes in the patterns of and returns to migration.

Table 9 looks at the results by municipal area, which is our proxy for urban/rural classification. There is some evidence here that the results are more associated with urban migrants. We see that none of the instrumented coefficients on weekly or hourly wages or weekly hours are statistically significant for the nonmunicipal group, even though this group has a larger sample. For municipal workers there are statistically significant negative effects on instrumented hours, although surprisingly, there is no effect on instrumented log weekly wages, despite the large negative impact on weekly hours, which implies a percentage fall in hours of 2.5% from an increase in population of 10%; thus, these results are mixed.

Tables A4–A6 look at the impact of migration on wages for self-employed workers in business and agriculture as well as comparing the results for both employees and the self-employed across the high and low seasons. These results (discussed in the appendix) are generally inconclusive. Our estimates for self-employed wage effects tend to be noisy in particular. Given the problems in measuring self-employed wages discussed earlier, this is perhaps unsurprising. Similarly, it is difficult to discern any pattern in the results by season.

C. *Comparing the Elasticities with Those from the Literature*

As we discussed in the introduction, there is a large literature estimating the impact of shocks in inward migration on native wages. While many do not explicitly consider hours, we can still compare our estimates of the elasticity of weekly earnings or hourly earnings from a change in migration with those from other studies. For internal migration, the estimates of Kleemens and Magruder (2014) for Indonesia suggest that a 1% increase in the population reduces native income by more than 1% when migration is instrumented. Maystadt et al. (2014) find higher estimates of a fall of around 5% in the real monthly wage of low-skilled workers in Nepal when labor supply increases by 1%; interestingly, statistically significant effects in wages are found for only formal sector workers. These estimates are higher than the instrumented estimates for weekly earnings of low-skilled workers contained in tables 6–8. These range from a 10% increase in population decreasing weekly earnings by 3.8% for low-skilled workers in table 8 for the period preceding the financial crisis to a decrease in weekly earnings of 8.1% for the narrower definition of low skill used in specification 1 of table 8.

The literature review (Sec. II) summarizes the results from the vast literature on international migration. Maystadt et al. (2014) examine Nepal, where the range of push and pull factors used to model migration inflows and outflows

TABLE 9

EFFECTS OF NET INFLOW RATE ON MALES: NONMUNICIPAL VERSUS MUNICIPAL AREA

	Nonmunicipal					Municipal				
	Employees	High Skilled	Low Skilled	Business	Agriculture	Employees	High Skilled	Low Skilled	Business	Agriculture
OLS:										
Log weekly wage	.011	−.050	.014	.141	.174	−.067***	−.069**	−.042	−.137**	−.220
	(.045)	(.089)	(.054)	(.128)	(.144)	(.025)	(.035)	(.032)	(.069)	(.276)
R^2	.569	.606	.511	.223	.444	.616	.648	.427	.220	.531
IV:										
Log weekly wage	−.353	−.337	.030	3.638*	3.052	.022	−.088	.098	.209	−2.707
	(.683)	(.741)	(.947)	(2.140)	(3.007)	(.097)	(.131)	(.143)	(.340)	(3.952)
R^2	.569	.606	.511	.209	.437	.616	.648	.427	.220	.523
OLS:										
Log hourly wage	.022	−.019	.022	.179	−.248	−.110**	−.118**	−.088*	−.192**	−.117
	(.048)	(.094)	(.058)	(.127)	(.166)	(.044)	(.057)	(.051)	(.082)	(.320)
R^2	.544	.604	.450	.186	.491	.623	.652	.411	.199	.566
IV:										
Log hourly wage	−.115	−.410	.322	3.766*	5.003	.164	−.021	.302*	.469	−1.214
	(.678)	(.797)	(.943)	(2.138)	(3.946)	(.124)	(.150)	(.173)	(.373)	(4.571)
R^2	.544	.604	.450	.171	.470	.623	.652	.410	.197	.565
OLS:										
Weekly hours	−2.560	−2.613	−2.542	−1.117	18.153***	1.988	1.554	2.650	3.379	−2.200
	(1.817)	(2.465)	(2.306)	(2.212)	(2.879)	(2.193)	(2.258)	(2.789)	(2.272)	(6.619)
R^2	.114	.136	.108	.043	.289	.158	.170	.121	.030	.297
IV:										
Weekly hours	−13.863	1.791	−5.434	−12.559	−62.720	−8.450**	−3.492	−13.243**	−15.021*	−84.082
	(16.652)	(18.014)	(23.172)	(22.657)	(60.354)	(4.212)	(3.821)	(5.991)	(7.970)	(73.020)
IV:										
Elasticity weekly hours	−.268	.036	−.104	−.233	−1.223	−.167	−.072	−.253	−.266	−1.791
R^2	.113	.136	.108	.042	.253	.155	.169	.116	.027	.237
Observations	115,102	26,542	88,560	97,416	176,627	79,308	37,819	41,489	86,299	5,783

Note. Regressions are estimated using individual data from the Thai Labour Force Survey from 1991 to 2000. Standard errors are clustered by provinces and waves. Dummies for salary period of payment (hourly, daily, weekly, and monthly) are introduced. For weekly wage regressions, we introduce the number of weekly working hours and its squared term. With the instrumental variable technique, we include the net instrumented migration rate specific for each subsample. IV, instrumental variables; OLS, ordinary least squares.

* Significance at 10% level.

** Significance at 5% level.

*** Significance at 1% level.

TABLE 10
PROBABILITY OF WISHING TO WORK MORE HOURS

	Employees		Business		Agriculture	
Variables	OLS	IV	OLS	IV	OLS	IV
Net inflow rate	.086***	.241*	.108***	−.056	−.029	−2.250
	(.029)	(.129)	(.023)	(.208)	(.073)	(1.437)
Observations	182,085	182,085	173,482	173,482	169,000	169,000
R^2	.072	.072	.036	.035	.063	.016

Note. Robust standard errors in parentheses. IV, instrumental variables; OLS, ordinary least squares.
* Significance at 10% level.
*** Significance at 1% level.

across regions includes weather, but also historical migration trends, measures of civil unrest and of environmental degradation. They show that inward migration leads to lower wages for formal sector natives as well as a loss of employment and rise in unemployment for lower skilled natives.

As noted earlier, there is a vast empirical literature looking at the impact of international migration on native wages. Borjas (2015) stresses that an important lesson that has been learned from this literature is the importance of comparing an influx of new migrants with a control group of natives with similar skills and found that if labor supply of high school dropouts increases by 1%, weekly wages of native high school dropouts fall by between 0.5% and 1.5%. Many other papers find little or no effects on native wages, and the explanation given in studies such as Manacorda et al.'s (2006) and Ottaviano and Peri's (2012)—which explain the absence of wage effects for natives by presenting evidence that migrants are imperfect substitutes for natives—has become an important tenet of the literature. Since we focus on low-skilled workers moving within the same country, arguably we deal with the concern that migrants need to be compared with natives with similar skills in an effective way. Unsurprisingly, given this we find negative effects on weekly earnings. Our estimates are smaller than those in Borjas but substantial when compared with much of the literature. For example, Friedberg and Hunt (1995, p. 42) in their review of this literature conclude that "a 10 percent increase in the fraction of immigrants in the population reduces native wages by at most 1 percent."

V. Conclusion

Bryan, Chowdhury, and Mobarak (2014) provide convincing evidence of large positive returns to internal migration in Bangladesh, demonstrating the potential importance of freedom of movement in enhancing the welfare of low-skilled workers. In this paper we have examined the impact of net inward migration on local labor markets in Thailand, specifically focusing on weekly wages and hours worked. To this end we constructed a data set of regional migration flows and individual labor market outcomes for the period 1991–2000 using the Thai Labour Force Survey. Our results show that instrumenting for the possible endogeneity of net inward migration is crucial to the analysis. The results suggest that wages of low-skilled male workers are highly flexible, with substantial adjustments in hours worked and weekly wages in response to short-term changes in labor supply. We find no effect on high-skilled workers. One possible explanation may be that hours and wages are slower to adjust for skilled workers because of implicit contracts, firm-specific capital, or other institutional features that limit firms' ability or willingness to adjust wages in response to possibly temporary shock.[25] Another possibility is that if there is a degree of imperfect substitutability between natives and migrants that this is only the case among higher-skill groups, as Card (2009) suggests, our definition of high skill possibly includes substantial heterogeneity in skill levels within the group.

While there is a large literature estimating the impact of migration on wages, typically such studies do not consider variations in hours per period. The empirical results presented here suggest that at least in some cases reductions in hours worked may be driving the reduction in weekly wages so that ignoring the impact on hours may provide an incomplete picture of migration on the local labor market. For example, in the Thai context, if we restricted our analysis to hourly wages, the empirical results would suggest that migration does not affect wages, while in fact there are substantial changes in weekly earnings associated with hours.

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[25] See Beaudry and Dinardo (1991) for an example and some evidence for an implicit contracts model, while Hall (2005) shows that the local monopoly rents in a search-matching model mean that wages can be sticky without violating rationality.

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