Labour Market Responses To Immigration:

Evidence From Internal Migration Driven By Weather Shocks*

Marieke Kleemans and Jeremy Magruder

February 2017

Abstract

We study the labour market impact of internal migration in Indonesia by instrumenting migrant flows with rainfall shocks at the origin area. Estimates reveal that a one percentage point increase in the share of migrants decreases income by 0.97 % and reduces employment by 0.24 percentage points. These effects are different across sectors: employment reductions are concentrated in the formal sector, while income reduction occurs in the informal sector. Negative consequences are most pronounced for low-skilled natives, even though migrants are systematically highly skilled. We suggest that the two-sector nature of the labour market may explain this pattern.

JEL Classification: J21, J61, O15

* Corresponding author: Marieke Kleemans, Department of Economics, University of Illinois at Urbana-Champaign, 1407 W. Gregory Drive, Urbana, IL 61801, USA. Email: kleemans@illinois.edu.

We are grateful to Max Auffhammer, Michael Anderson, Sam Bazzi, Marshall Burke, David Card, Michael Clemens, Edward Miguel, Sofia Villas-Boas, Dean Yang, and seminar participants at numerous presentations. We gratefully acknowledge financial support from the U.C. Berkeley Population Center and Kleemans acknowledges support from the AXA Research fund, and Magruder acknowledges support from the National Institute of Food and Agriculture. All errors are our own.

Public debate often expresses concerns that immigrants take the jobs of natives and increase labour market competition, which causes wages to fall. While this debate is global, the academic literature has concerned itself primarily with immigration to high-income countries, with particular attention given to Mexican immigration to the United States. Even though consensus within this literature remains somewhat elusive, we know even less about the labour market impacts of internal migration in developing countries.

We might anticipate these labour market impacts to be quite different for several reasons. First, the costs of migrating internally are much lower than the costs of international migration, which may allow migration to respond more quickly to favorable labour market conditions and affect the number and characteristics of migrants. Secondly, labour markets in developing countries are structurally quite different from the United States. The conventional characterization of developing country labour markets features a heavily regulated formal sector which coexists with an uncovered informal sector, exhibiting lower wages and productivity (e.g. Harris and Todaro, 1970). The effects of an increase in labour supply on working conditions may be quite different as labour supply puts pressure on both of these sectors, which could change both wages within a sector as well as the availability of labour market opportunities across sectors. Finally, relatively thin markets may limit the firm's capacity to adapt to a surge (or reduction) in labour supply by relocating or entering new markets, and thereby potentially increase the magnitude of labour market responses.

Despite the difference in potential mechanisms for labour market effects of immigration, estimating the effects of internal migration in developing countries retains the primary econometric concern that has challenged estimates of Mexico-U.S. migration. That is, regressing labour market outcomes on immigrant stocks may be confounded by the tendency of migrants to be attracted to areas with better labour market opportunities, often referred to as the "moving to opportunity bias". OLS estimates of labour market impacts of migration are therefore likely to be biased in the positive direction. This paper uses an instrumental variable approach to address this issue. Using the Indonesia Family Life Survey, we document the migration decisions of almost 29,000 individuals within Indonesia over 13 years. We use these empirical migration patterns to form catchment areas of origins that send migrants to each destination district. We then generate exogenous variation in the number of migrants in each district using rainfall shocks in these catchment areas, following

Munshi (2003).

We find that a one percentage point increase in the share of migrants decreases natives' average income per hour by 0.97 % and reduces the employment rate of natives by 0.24 percentage points. We show that, as expected, the negative effects using IV-2SLS are larger than OLS estimates.[1] The wage estimates are very similar in magnitude to those reported for the U.S. in Borjas (2003). However, the distribution of the effects is different in two important ways. First, the negative income effects are concentrated in the informal sector, with a 1.84 % decrease of informal sector income, and the employment effects are largest in the formal sector at 0.33 percentage points. This distinction between sectors provides direct evidence in support of the conventional characterization of how a two-sector labour market responds to an increase in labour supply, and is consistent with other evidence on the importance of binding wage floors in the formal sector in 1990s Indonesia (e.g. Alatas and Cameron, 2008; Magruder, 2013).

Second, we find that the negative labour market effects of immigration are most pronounced for those with lower levels of education. This finding is consistent with earlier studies on the U.S. that have attributed this pattern to increased substitutability between low-skilled immigrants and low-skilled natives. Unlike in those studies, however, the pool of internal migrants in Indonesia is relatively high-skilled, at least in terms of education levels. We discuss a number of reasons why poorly educated Indonesians may be disproportionately affected by an influx of highly-educated migrants. We find little evidence that this result could be explained by differences in the returns to skill between migrants and natives, such that highly-educated migrants are more substitutable to low-educated natives in terms of skill level. We also do not find support for the hypothesis that this result is driven by differences between average treatment effects of migrants in general and local average treatment effects of weather-induced migrants that we estimate. Instead we propose that this result may be understood as another consequence of the two-sector labour market with a wage floor in the formal sector where the less-skilled group faces chances of disemployment or employment in the informal sector.

The identification assumption underlying our estimation strategy is that precipitation in the

[1] In fact, the difference between OLS and IV-2SLS estimates are larger than the effects typically found in the U.S.-Mexico literature, which may be because there is a larger "moving to opportunity bias" for these domestic migrations.

migration origin areas does not affect local labour market at migrant destination areas once precipitation at the destination itself is controlled for. A concern that may arise is that rainfall measures at the origin areas are correlated with wages or employment in destination areas through channels other than migration. This would constitute a violation of the exclusion restriction and may occur due to local trade, for example of agricultural products, which could affect labour market conditions at the destination. We test for the exclusion restriction by restricting our analysis to migration over longer distances. If the effects were driven by local trade channels, we would expect the magnitudes of our results to reduce as the intensity of trade and economic linkages decreases with distance. In contrast, our results in Section 5 document that labour market impacts are stronger using only longer distance migrants. In this section we also use simulations to test if serial correlation within the catchment area could drive our results and show that the exact migration patterns we observe – and not other correlated patterns, for example those created by local trade – are responsible for our results.

A large number of studies have estimated labour market impacts of immigration in OECD countries, especially in the case of migration from Mexico to the United States. An overview of the literature is provided by the survey articles Okkerse (2008) and Kerr and Kerr (2011). While the literature on high-income countries is vast, fewer related studies have been carried out in a developing country context. Two exceptions are Bryant and Rukumnuaykit (2007), who found that immigration in Thailand reduced wages but did not adversely impact employment, and Strobl and Valfort (2015) who find adverse employment effects in Uganda, especially in areas with low capital mobility.[2] Despite the large focus on OECD countries, fears that immigrants increase unemployment and lower wages are expressed not only in high-income countries, but also in less developed countries. Comparing 86 countries with varying levels of income per capita, Kleemans and Klugman (2009) find that negative attitudes towards immigrants are most pronounced in middle income countries. Indonesia ranks second out of 46 countries in terms of preferences to limit or prohibit immigration, with only Malaysia ranking higher.

While most earlier work studies international migration, this study focuses on internal migra-

[2] Strobl and Valfort (2015) was developed contemporaneously to this paper and also uses weather shocks as a source of exogenous variation. It differs from this paper in its context, its focus on infrastructure and capital stocks, and in abstracting away from frictions in a two-sector labour market.

tion.[3] The absence of crossing an international border is likely to affect the number, type, and possibly the labour market impact of immigrants. Despite frequent discussions about migrants from developing countries entering developed countries, the overwhelming majority of migrants move within developing countries. Bell and Charles-Edwards (2013) estimate that world-wide there are approximately 763 million internal migrants compared to 214 million international migrants (UNDESA, 2013), and Deb and Seck (2009) estimate that one out of four Indonesians live parts of their lives in a district different from their place of birth, which translates to over 60 million internal migrants.

Indonesia – like other developing countries – also distinguishes itself from the OECD countries considered in prior work through the coexistence of a large informal sector and a formal sector characterised by strict labour market regulation. In the 1990s, minimum wages in Indonesia tripled in nominal terms and doubled in real terms to reach the 38^{th} percentile of wages for full-time workers in the Indonesia Family Life Survey data in 1997. Other work, such as Alatas and Cameron (2008) and Magruder (2013), document that these minimum wages were binding on at least part of the labour force. As we find in this paper, the two-sector labour market in Indonesia results in different effects of large scale migration on labour market outcomes for natives.

We open this paper by motivating the empirical strategy in Section 1 and describing the data in Section 2. The main results are presented in Section 3 and Section 4 explores heterogeneous labour market effects by skill level. Robustness checks are presented in Section 5, and Section 6 concludes.

1 Empirical Strategy

This paper uses weather in the migrant's origin area as an instrument to get exogenous variation in the number of migrants entering a destination area. Our approach follows Munshi (2003) who studies network effects amongst Mexican immigrants in the U.S. This instrument may be successful if economic outcomes depend on rainfall, which is the case in Indonesia as many Indonesians depend on rainfed agriculture and various studies have shown that higher rainfall raises agricultural

[3] In doing so, it builds on work by Boustan *et al.* (2010), who examine labour market effects of internal migration in the U.S. during the Great Depression.

productivity, income and wealth (Kishore *et al.*, 2000; Levine and Yang, 2014; Kleemans, 2017).

Intuitively, the first stage is meant to capture the following process: If a particular destination area d hosts immigrants from origin area o, then we expect that a negative rainfall shock in origin area o will drive people to destination area d. This gives exogenous variation in the number of immigrants in a destination area. In the estimation, we use individual-year pairs as units of observation. In equation form, the share of people who are migrants in each destination area at time t, $migrants_{dt}$, is regressed on rainfall in the origin areas.[4] Each destination area d, hosts migrants from a number of origin areas, which we refer to as the 'catchment area' of that destination, defined as $C(d)$. The first stage can be expressed by the following equation:

$$migrants_{dt} = b_1 \sum_{o \in C(d)} (w_o rainfall_{o,t-1}) + b_2 * rainfall_{d,t-1} + X_{it}c + d_t + a_d + e_{dt} \tag{1}$$

Unlike Munshi (2003), we take rainfall in the entire catchment area of each destination into account. This is captured through the summation in equation (1), where w_o is the weight of origin area o, which is proportional to the share of migrants from origin area o in destination area d. Weights are determined by the share of migrants from that origin area in destination d during the 13 years preceding our sample (1975 - 1987) and are fixed over time. Section 5 shows that the results are robust to various alternative definitions of the origin area weights, w_o, including weights that are based on migration patterns during our 13 year study period (1988 – 2000) and weights that are based on census data. All specifications control for rainfall at the destination, $rainfall_{d,t-1}$, to account for possible correlation between origin and destination rainfall and the direct impact of destination-level rainfall on the labour market in the second stage. X_{it} are control variables that include dummy variables for gender, age group and education level. Our main analyses are run at the individual level, allowing us to use individual-level control variables to increase precision. As robustness checks we run all analyses in a dataset in which all variables are collapsed to the destination level, including the control variables. In this case, X_{it} is replaced by X_{dt} representing average destination-level values of the control variables gender, age and education level. In both

[4] Note that $migrants_{dt}$ is the ratio of the stock of migrants to the stock of people at the destination, not the year-to-year change in the number of migrants.

cases, standard errors are clustered at the destination level, and Section 5 and Table A8 discuss alternative methods of clustering. d_t and a_d represent time and destination fixed effects and e_{dt} is the error term. By weighing origin-level rainfall using only time-invariant migration patterns, we ensure that whichever labour market characteristics affect those patterns will be absorbed by the destination fixed effects a_d. In addition to destination fixed effects, we run robustness checks including individual fixed effects. While equation (1) shows the first stage when using rainfall in year $t-1$ as an instrument, we experiment with several lagged variables and various measures of weather as discussed in Section 5.

Given that negative rainfall shocks in the origin area drive people to a destination area, the second stage asks whether this changes individual labour market outcomes in the destination area at time t. This paper studies the labour market impacts on natives, i.e. non-migrants. The second stage is given by

$$Y_{it} = \beta_1 \widehat{migrants}_{dt} + \beta_2 * rainfall_{d,t-1} + X_{it}\gamma + d_t + a_d + \varepsilon_{dt} \tag{2}$$

Y_{it} refers to the individual-level labour market variables of interest. We look at the effects on income and employment, overall as well as in the formal and informal sector. $\widehat{migrants}_{dt}$ are the predicted values from the first stage. $Rainfall_{d,t-1}$ and X_{it} contain the same set of control variables as in the first stage, d_t and a_d are time and destination fixed effects and ε_{dt} represents the error term.

The main assumption underlying this approach is the exclusion restriction, which states that the only channel through which rainfall in the origin area affects labour market outcomes in the destination area is through changes in the share of immigrants. Given that we have controlled for destination area rainfall and that deviations from historical rainfall patterns are hard to predict, this restriction amounts to assuming that local rainfall is a sufficient statistic for the direct effects of global rainfall patterns on labour market outcomes. We test the robustness of this assumption by considering only long-distance migration in Section 5. We also test whether migration patterns *per se* are important in summarizing the effects of nearby rainfall on destination labour market conditions or whether alternate patterns of spatial correlation would be likely to deliver similar estimates. Furthermore, as with any instrumental variables approach, the estimated effects will be local average treatment effects (LATE). This means that the labour market impacts are estimated for those immigrants that are induced by weather shocks. Section 4 explores how weather-induced migrants compare to average migrants.

2 Data

2.1 *Migration and Labour Market Data*

Limited data availability has prevented earlier studies from obtaining empirical evidence on migration in developing countries as such studies require data collection across regions and across time. In most panel datasets, migrating individuals attrite from the panel, which hinders inference. This study uses the Indonesia Family Life Survey (IFLS) as the main data source, a panel dataset that is known for relatively low rates of attrition. This longitudinal survey is representative of about 83 % of the Indonesian population and contains individuals living in 13 of the 27 provinces of the country (Strauss *et al.*, 2004). The analyses are based on the first three waves of the IFLS, which covers the 13 year period from 1988 to 2000.[5]

Attrition is low in the IFLS: re-contact rates between any two rounds are above 93 percent, and 91 percent of the original households were contacted in all three rounds (Strauss *et al.*, 2004). Low attrition and intensive efforts to track respondents from the original sample makes the IFLS particularly suitable for migration analysis. In addition to migration data, the dataset contains extensive information on the respondents' labour market outcomes, education, and other characteristics.

Using the migration modules of the IFLS, a dataset is obtained of 28,766 individuals, who recorded when and where they migrated after the age of 12. In addition to migration data that is based on recall between waves, the dataset contains information on where respondents were born and where they lived at age 12. This information is transformed into a panel dataset that reports the person's location in each year. This results in a panel dataset of individual location decisions and labour market outcomes from 1988 to 2000 with a total of 192,237 individual-year observations.

[5] The fourth and fifth wave, carried out in 2007/2008 and 2014/2015, respectively, are not included in the sample because no recall data was collected on annual income, and the answer categories of sector of employment changed and became incompatible with earlier waves.

Table 1 provides summary statistics of this dataset.

Education is defined on a scale from 0 to 4, ranging from no education (0) to university education (4). While imperfect, education is used to determine a person's skill level: If a person has obtained at least some high school education (education value of 2), he or she will be defined as 'high-skilled', while those with no or only primary education are referred to as 'low-skilled'. This cut-off is chosen because it leads to the most even split between low and highly-educated individuals.

The main labour market variables in the current study are income and employment, overall and in the formal and informal sectors. All these variables are defined at the individual level and based on recall data in between waves, leading to labour market outcomes being observed for each year of the panel. Income is recorded as log income per hour in Indonesian Rupiah[6] and the employment variable indicates whether a person is working, as opposed to housekeeping, going to school, being unemployed or retired etc. The overall employment rate is 79 % and 52 % of the sample is self-employed. While imperfect, this variable is used to characterise the informal sector as self-employed individuals are more likely than wage workers to work informally. Income per hour in the formal sector is the monthly wage divided by the reported hours worked, and income per hour in the informal sector is calculated by dividing monthly profits by hours worked for the self-employed.[7] The IFLS asked for the respondent's main and side job, so an individual may simultaneously have a job in the formal sector and another job in the informal sector, in which case they count as being employed formally and informally at the same time.

Throughout this study, a migrant is defined as a person who does not live at his or her place of birth, as opposed to natives who still live where they were born. Although other definitions have been explored, this is the most commonly used definition in the literature (UNDP, 2009). For each destination we count the number of migrants in each year and call this the migrant stock. This number is divided by the total population in that destination to get the migrant share of the population, which is used as the main migration variable in this study. Location information is available for three geographical levels. The largest level is the province of which there are 34 in Indonesia. These are further divided into districts (Kabupaten) and sub-districts (Kecamatan).

[6] All monetary values are price adjusted using the annual consumer price index with base year 2000 provided by the International Financial Statistics of the International Monetary Fund (IMF, 2017).

[7] The top one percent of reported income observations are considered outliers and disregarded.

This study defines districts (Kabupaten) as separate geographical units, meaning that a migrant is someone who is not born in the district they live in. While sub-districts could have been chosen instead, these are often small geographical units of which there are more than 6,500 in Indonesia. This would mechanically create a large number of migrants, some of whom only move over a short distance and may not consider themselves migrants. The final dataset contains 205 districts hosting 28,766 individuals.[8]

Comparing natives and migrants in Table 1 reveals that internal migrants in Indonesia are systematically higher skilled as measured by education level than most natives. Native's hourly wage is 29 % lower than that of migrants, and migrants work more hours per week. While overall employment rates of natives and migrants are comparable at 79 %, migrants are 10 percentage points more likely than natives to work in the formal sector (47 % and 37 %, respectively).

Measurement of overall labour market impacts is challenged by the fact that the pool of employed people is changing as immigrants arrive and leave. Migrants who recently arrived may still be looking for work or may initially have to settle for a lesser-paying job, which would mechanically push coefficients in the negative direction. In order to deal with this potential bias, we estimate labour market impacts on natives only.

2.2 *Weather Data*

Weather data are obtained from the Center for Climatic Research of the University of Delaware (Matsuura and Willmott, 2009). Monthly estimates of precipitation and temperature are available for grids of 0.5 by 0.5 degree, which is approximately 50 by 50 kilometers on the equator. These data are based on interpolated weather station data and are matched to IFLS household locations using GIS data. Figure 1 shows the survey locations of the IFLS on a map of Indonesia as red dots and the blue grids represent the weather data that the locations are mapped to.

While this study explores various weather measures, precipitation z-score is used as the main weather variable. Z-scores are obtained by subtracting the precipitation mean and dividing by the

[8] As shown by Bazzi (2016), weather shocks also induce international migration out of Indonesia. However, the IFLS does not include these moves, so we are not able to incorporate the international dimension. The third wave in 2000 was the first to ask if Indonesia was the country of previous migration and showed that this is the case for 98.41 % of reported moves. For the remaining 1.59 %, the country information is either unknown or missing.

standard error. This is in line with Maccini and Yang (2009) who argue that rainfall is the most important source of weather variation in Indonesia. Figure 2 shows how average precipitation varies across years. Temperature shows less variation over time due to Indonesia's equatorial location. Lagged weather variables are used to allow for a lagged response to bad weather shocks. Instead of using annual data from each calendar year, all measures are created from July until June in the year after to reflect the growing seasons in Indonesia. All analyses are repeated using calendar years, which does not significantly change the results (results not shown).

In addition to precipitation z-scores, this study carries out robustness checks with various other weather variables. Precipitation levels and temperature are used, as well as precipitation squared and cubed to allow for nonlinear effects. To capture unusual weather patterns, deviations from the mean and growth are used. Finally, variables for extreme weather events are created. Droughts are defined as seasons in which precipitation is less than a standard deviation below the mean, and floods as seasons in which precipitation is more than a standard deviation above the mean. The next section describes the results using precipitation z-scores and Section 5 discusses the robustness of these results when using a range of alternative weather variables.

3 Results

3.1 *Migrants' Responsiveness to Weather Shocks*

The first stage analysis examines whether people are more likely to leave the place they live after negative weather shocks. Table 2 shows the first stage results using various sets of rainfall lags. Origin-level precipitation z-scores, shown in the upper part of the table, are summed up over the catchment area of each destination according to equation (1). As explained in Section 1, all specifications include the same number of lags of destination rainfall, shown in the lower part of the table, to control for possible correlation between origin and destination weather measures and a direct impact of destination-level rainfall on the labour market. All regressions include socio-economic control variables as well as time and destination fixed effects, and standard errors are clustered at the destination level.

The results consistently show a significant negative coefficient on origin area rainfall measures, indicating that people are more likely to migrate in response to lower rainfall. The coefficients on rainfall at time $t-1$ are largest and highly significant, which is in line with the basic intuition that people respond to bad weather shocks with a slight lag. Note that, as discussed in the previous section, rainfall in year $t-1$ starts in July of year $t-1$ and ends in June of year t, so as expected this creates the largest migratory response in year t. The F-statistic of joint significance when using only lagged rainfall in the second column is sufficiently high, at 22.76.[9] Therefore, lagged precipitation will be used as the main instrument. Column 6 correctly finds that future rainfall does not have any predictive power.

Destination rainfall measures are only used as control variables rather than instruments to avoid violating the exclusion restriction, as there are likely other channels through which weather shocks at the destination affect labour markets at the same location. The coefficients on rainfall at the destination are positive and significant, and slightly smaller in magnitude than the coefficients on origin rainfall. This may suggest that positive weather shocks at the destination are a pull factor to migrants, to a slightly lesser extent than bad weather shocks at the origin are a push factor. Destination rainfall measures are used as control variables in all remaining analyses.

Table A1 in the Appendix compares our main instrument (column 1) to alternative specifications of the first stage. Results are broadly similar when using individual fixed effects instead of destination fixed effects (columns 2 and 4) and precipitation levels instead of z-scores (columns 3 and 4). Appendix Table A4 shows results using longer lags of rainfall and reveals that rainfall remains significant for four years but that the F-statistic of joint significance reduces. The overall labour market estimates in columns 3 and 4 are similar but preference is given to specifications with stronger predictive power of the first stage relationship.

3.2 *Labour Market Response to Immigration*

Using exogenous variation in the number of migrants entering a destination area caused by weather shocks in the origin areas, this section investigates whether increased labour market competition affects income and employment at the destination.

[9] This F-statistic surpasses the Stock and Yogo (2005) critical value for a test of maximal size 0.1.

First, OLS regressions are carried out of the reduced-form relation between rainfall at the origin areas and labour market conditions at the destination. If increased numbers of immigrants, induced by negative weather shocks, reduces income and employment, then we expect this reduced-form relationship to be positive. The first column of Table 3 shows the reduced-form relationship between precipitation and average log income per hour, and the second column shows the relation between precipitation and employment. Both columns confirm the prediction of a positive reduced-form relationship.

The first stage has established that negative rainfall shocks in origin areas increase the likelihood of migrating. This exogenous variation in migrant stock is used to study labour market responses in the second stage. Table 4 shows the main second stage results and compares them to OLS regressions in the first and third column. The first column shows that the coefficient on log income per hour is indistinguishable from zero when using OLS. This contradicts economic theory that predicts negative effects, but this result is likely due to the fact that a simple OLS regression is unable to isolate causal effects. As discussed earlier, OLS regressions may be biased in the positive direction due to the "moving to opportunity bias". Comparing column 1 to the IV-2SLS specifications in column 2 suggests that the "moving to opportunity bias" in the OLS is large enough to cancel out the negative causal estimates that are revealed using the preferred IV-2SLS specifications. Column 2 indicates that an increase in the migrant share of the population by 1 percentage point reduces average income by 0.97 %.[10] In the IFLS data, the average share of migrants at a destination is 15.8 % so this corresponds to a 6.3 % increase of the current migrant share.

It is worth noting that the difference between OLS and IV-2SLS estimates is larger in this study than the difference typically found in the literature on Mexican immigrants entering the U.S. One interpretation is that the "moving to opportunity bias" is larger in our study, which may be caused by the fact that internal migrants face fewer social and physical barriers to migrate, including no international border to cross.

The last two columns of Table 4 show that an increased proportion of immigrants reduces

[10] By means of comparison, Borjas (2003) also finds that a 1 % increase in the share of migrants is associated with wage decreases of 0.919 %.

employment. Comparing the OLS specification in column 3 to the IV-2SLS regression in column 4 again suggests the existence of a "moving to opportunity bias" in the OLS specification. Column 4 shows that increasing the share of immigrants by 1 percentage point reduces the employment rate by 0.24 percentage points.

3.3 *Labour Market Effects Across Sectors*

Indonesia's labour market in the 1990s can be characterised by a competitive informal sector and a formal sector with high and binding minimum wages, as described in more detail in the next section. If wages are determined competitively in the informal sector and affected by a wage floor in the formal sector, we would anticipate different effects of migration in these two sectors. We test for this possibility in Table 5 and confirm that the effects differ across sectors: a one percentage point increase in the migrant share reduces income in the informal sector by 1.84 %, while no adverse income effects are found in the formal sector. Conversely, a percentage point increase in the migrant share reduces formal sector employment by 0.33 percentage points while no employment effects are found in the informal sector.[11] [12] Appendix Tables 2 and 3 repeat this analysis using precipitation levels instead of precipitation z-scores as instruments. The results are broadly similar to those in Table 5.

These results provide support for the two-sector characterization, and for the hypothesis that wage minima bind and affect the number of jobs: when labour supply increases, we observe some workers get crowded out of the formal sector. We similarly observe that workers in the informal sector receive lower wages, consistent with the hypothesis that those wages are set competitively.

[11] The difference between formal and informal sector income is statistically significant with a p-value of 0.0207, but the difference between formal and informal sector employment is not statistically significant ($p = 0.5044$).

[12] The formal sector responses recall results by McKenzie *et al.* (2014) who find that international migrants from the Philippines similarly respond to destination GDP fluctuations on the quantity dimension without related wage responses. Both their model and the model in the next section attribute this response to the presence of a binding minimum wage, though they find different heterogeneity by skill level. Interestingly, the differences in heterogeneous responses by skill level between this context and theirs could also be attributed to differences in minimum wage context: they argue that visa requirements amount to multi-tiered wage minima across skill levels while we argue that the presence of an unregulated sector influences responses by skill level.

3.4 *Selection and Wage Effects*

Since employment and wages are changing contemporaneously with migration, wage effect estimates will encompass the net effects of both any direct causal impacts of the immigration and any selection effects on the pool of the employed. These selection effects seem likely to be positive (assuming relatively low wage individuals are more likely to be displaced, which will be confirmed in the next section), so our estimates could be interpreted as conservative. However, if the selection is heterogeneous across individual characteristics which do not change over time, adding individual fixed effects into the estimation equation will allow consistent estimation of the causal impact of immigration on wages. Estimates with individual fixed effects are presented in Table 6; point estimates of wage effects become slightly larger, consistent with the idea that there may be a conservative bias caused by selection.

4 Heterogeneity by Skill Level

In the previous section, we have established that native workers are on average negatively impacted by an influx of migrants. We may anticipate that these negative impacts will be borne heterogeneously by workers of different skill levels. A motivation for this insight is given in the labour market model developed by Card and Lemieux (2001) and Borjas (2003), which develops responses to immigration in an intuitive, single-sector, competitive labour market.

Suppose aggregate output in the economy, y, is a function of capital, K, and labour, L, and given by the following production function:

$$y = K^{1-\alpha} L^{\alpha}$$

with $0 < \alpha < 1$. Labour supply L aggregates n types of labour with substitutability parameter v, so that

$$L = \left(\sum_{k=1}^{n} \theta_k L_k^v \right)^{1/v}$$

where $0 < v < 1$.

After substituting the labour supply equation into the production function, wages of group j

are determined by marginal products:

$$w_j = \frac{\partial y}{\partial L_j} = \alpha \theta_j K^{1-\alpha} L_j^{v-1} \left(\sum_{k=1}^{n} \theta_k L_k^v \right)^{(\alpha - v)/v}$$

In this set-up, we can examine how wage of group j changes as the amount of labourers of group g increases. Two types of comparisons here are particularly interesting: how wages change with an influx of workers of the same type and how wages change with an influx of workers of a different type. This framework quickly leads to three predictions, derived in the appendix:

$$1 : \frac{\partial w_j}{\partial L_j} < 0$$

$$2 : \alpha < v \Rightarrow \frac{\partial w_j}{\partial L_g} < 0$$

$$3 : \frac{\partial w_j}{\partial L_j} < \frac{\partial w_j}{\partial L_g}$$

The last statement conveys the basic intuition that groups that are similar to incoming migrants, and therefore demonstrate a larger degree of substitutability, face increased competition and in this model will be affected to a larger extent than groups that are more dissimilar from migrants.

Extrapolating to the Indonesian context, we have documented that internal migrants in Indonesia are more educated than native non-migrants. If labour markets in Indonesia respond similarly as the competitive markets in more developed countries, and if education is an effective proxy for skill, we would anticipate that highly-educated natives are most negatively impacted by migrants.

4.1 ***Empirical Estimates by Skill Level***

This section examines how the labour market effects of internal migration in Indonesia differ by skill level. Table 7 compares labour market effects of those with primary school education or less (uneven columns) to the effects on those who received higher levels of education (even columns), and performs these analyses across sectors (columns 1 and 2), for the formal sector only (columns 3 and 4) and for the informal sector only (columns 5 and 6). In contrast to model predictions, negative labour market effects are most pronounced for those with lower levels of education: increased competition in the formal sector drives low-skilled workers out of this sector, making them 0.32 percentage points less likely to be formally employed after a one percentage point increase in the migrant share. Formal employment impact for high-skilled individuals is smaller and insignificant. Similarly, a percentage point increase in migration reduces informal sector income by 2.47 % for the low-skilled, while no adverse income effect is detected for high-skilled individuals.[13]

In some ways, these results recall estimates from the literature on Mexico-U.S. migration, where the lowest-skilled natives are also disproportionately affected. In that context, this finding is usually interpreted as a substitution effect, because immigrants are similarly low-skilled. In the Indonesian context, however, migrants achieve higher levels of education than natives. This seems at odds with the results derived from the single sector, competitive labour market model. In the subsequent sections, we discuss several hypotheses that could explain our finding that low-skilled natives still face the largest negative labour market consequences from high-skilled migration.

4.2 *Measuring Skill Level*

First, it is possible that education is not the important dimension of skill in this setting, or is differentially important for natives and migrants, so that highly-educated migrants are most substitutable with less-educated natives. If this hypothesis were true, we might expect the returns to education to be lower for migrants than for natives. Table 8 shows Mincer-style regressions, using both the coarse educational categories we have used throughout in this paper (in columns 1-3) and a more conventional specification using a linear years of education variable (in columns 4-6). Focusing on columns 4-6, we see that an extra year of education is worth about 8 % more in earnings, which accords with similar analyses in other contexts. Moreover, whichever educational measure we use, we see that the returns to education are qualitatively similar for migrants and for natives (and in fact, larger for migrants). We conclude that the relationship between education and skill level is similar for migrants and for natives, as the difference in earnings between more-educated and less-educated migrants is at least as large as that for natives. Given that Table 1 already showed us that migrants earn on average higher incomes than natives, it seems implausible that

[13] The difference between low- and high-skilled workers is statistically significant overall ($p = 0.0582$), in the informal sector ($p = 0.0319$), but not in the formal sector ($p = 0.5082$). For employment, the differences between low- and high-skilled workers are not statistically significant.

migrants have on average lower skill than natives. We thus find little support for the hypothesis that education is not a relevant dimension of skill.

4.3 *Weather-Induced Migrants*

Second, it is possible that local average treatment effects (LATE) are different from average treatment effects in this context. Our estimates capture the effects of the type of migrants that responds to negative rainfall shocks, who may be different from the average migrants in our summary skill measures. Our first stage showed that individuals are more likely to engage in internal migration in response to bad rainfall; poorer individuals may respond this way due to an insurance motive (Kleemans, 2017), which could lead to our empirical results. Alternatively, richer people may respond to poor rainfall due to lower opportunity costs at home (Bazzi, 2016), which would render the patterns here even more striking. In Table 9, we test whether contemporaneous rainfall shocks also create a pool of migrants who are less educated compared to most migrants by restricting our sample to migrants and regressing an indicator variable for high education on origin rainfall measures. If the people who migrate when rainfall is poor have less education than migrants on average, we should see a negative and significant relationship between origin precipitation and migrants' education level. The point estimates on both contemporaneous and lagged precipitation are positive and mostly insignificant, suggesting that the LATE-complying migrants are not different on average from other migrants in terms of education.

4.4 *Dual-Sector Model*

Alternatively, it is possible that the two-sector labour market structure leads to different substitution patterns. In the beginning of this section, we maintained the assumption of competitive wage-setting in a single sector to replicate the Card and Lemieux (2001) and Borjas (2003) result that similar natives would be most negatively affected by migrants, a pattern which was rejected in our data. Here, we weaken the assumption to allow for a two-sector labour market.

The classical characterization of a two-sector labour market features a formal sector where wages are subject to binding labour regulations, resulting in a shortage of formal sector jobs (e.g. Harris and Todaro, 1970). This labour market institution is one of the main motivations for the presence of a large and competitive informal sector. To assess these features, suppose that in the formal sector $w_j \geq \hat{w}\ \forall$ j, where $\hat{w}$ represents a wage minimum. If workers are imperfectly substitutable ($v < 1$) then the formal sector will employ a mix of workers of different skill groups, at wages bounded below by $\hat{w}$. For some constrained groups, however, labour supply will outpace demand at the wage floor. For these groups, excess workers work in the informal sector, where workers of all types are homogeneously productive, and the production function is given by $\frac{1}{\gamma}L_I^{\gamma},\ \gamma \leq 1$. This production function incorporates the intuition that capital stocks are relatively unimportant in informal production, and allows for the possibility that limited local demand for informal products and services leads to decreasing returns to labour. They therefore earn $I \equiv L_I^{\gamma-1}$, with $I(L_I) < \hat{w}$. This case seems particularly relevant to 1990s Indonesia, where minimum wages were high and quickly growing, and there is a large and vibrant informal sector.[14] Here, we demonstrate that the key result of the Card and Lemieux (2001) and Borjas (2003) model – that individuals of the same skill group are most affected by immigration – no longer necessarily holds in labour markets with these features.

Returning to the model, consider group g who is constrained and some members of group g work in each sector. Suppose that $\hat{L}_g < L_g$ succeeds in finding formal employment. In that case,

$$\hat{w} = \frac{\alpha\theta_g K^{1-\alpha}}{\hat{L}_g^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu}$$

$$\hat{L}_g = \left[\frac{\alpha\theta_g K^{1-\alpha}}{\hat{w}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu}\right]^{1/(1-\nu)}$$

and mean wages for group g are

$$\bar{w}_g = \frac{I(L_g - \hat{L}_g) + \hat{w}\hat{L}_g}{L_g}$$

Note that now, the changes in wages for group g in response to an influx of group j is

$$\frac{\partial \bar{w}_g}{\partial L_j} = \frac{\hat{w} - I}{L_g}\frac{\partial \hat{L}_g}{\partial L_j} + \frac{(L_g - \hat{L}_g)}{L_g}(\gamma - 1)\frac{I}{L_I}\frac{\partial L_I}{\partial L_j}$$

[14] For a description of wage minima in 1990s Indonesia see, e.g., Alatas and Cameron (2008) or Magruder (2013).

There are therefore two effects of an influx of group j on constrained group g. First, the fraction of group g workers in the formal sector may change. Since formal sector wages are higher, this changes the average wage of group g. Second, the wage rate in the informal sector may change due to a change in the labour supply to that sector.

This observation leads to the following predictions, all focused on the case where $\alpha < v$. Proofs can be found in the Appendix.

1. An increase in immigration from any unconstrained group will decrease formal employment for the constrained group $g(\frac{\partial \hat{L}_g}{\partial L_{g'}}) < 0$. Since group g is constrained, formal sector wages will stay constant.

2. An increase in immigration from any unconstrained group will (weakly) decrease wages in the informal sector.

3. For some parameterizations, the mean effect on immigration of unconstrained group j on wages of group g will be larger than the effect on own-group wages. If labour has a constant marginal product in the informal sector ($\gamma = 1$), then effects on group g will be larger if

$$w_j(1-v) < \frac{(\alpha - v)\theta_j L_j^v}{(\sum_{k=1}^n \theta_k L_k^v)} \left[w_j - \left(\frac{\widehat{w} - I}{1-\nu} \right) \frac{\hat{L}_g}{L_g} \right] \tag{3}$$

With a declining marginal product in the informal sector, this bound is conservative, that is, the range of parameters which produce larger out-group effects is larger.

Inequality 3 is guaranteed to be satisfied if $\nu \to 1$, and for any given set of parameter values where $\alpha < \nu$, there exist values of ν, strictly less than 1, which satisfy this equation. Moreover, we note that as $\theta_j L_j$ increases relative to the overall size of the effective labour force, the set of values of ν that cause a greater change in wages for low-skilled groups grows. This may be the case in our empirical analysis, as we compare low- and high-skilled workers, each of which constitute about half of the total labour force. Low-skilled natives resemble group g in the model, which is adversely impacted by the minimum wage in the formal sector, while employment opportunities for high-skilled natives in the formal sector are unaffected.

An ideal test for this mechanism would examine whether elasticities of employment of low-skilled workers to immigration are indeed higher in places where minimum wages bind more tightly. For our identification strategy to work, we would need the extent to which minimum wages bind to be either fixed over time (and so collinear with fixed effects) or for changes in the bind of the minimum wage to be exogenous. Unfortunately, neither of these are plausible in the Indonesian context there is tremendous churning in the bind of minimum wages in districts over time,[15] and this variation was purposely intentioned to respond to innovations in local economic conditions.

As such, in this section we develop a number of summary statistics to demonstrate that the underlying assumptions of the dual sector model are met rather than examining a direct test. A first necessary condition is that high-skilled workers (the unconstrained group in the model), should be more likely to be employed in the formal sector than low-skilled workers (the constrained group). In the data, this difference is large: 72 % of highly-educated workers have formal sector jobs compared to 48 % of low-educated workers. Second, the model predicts that it is possible for an increase in highly-educated workers to disproportionately affect low-educated workers when the substitutability between worker types is high. To assess the substitutability between low- and high-skilled workers, we examine what fraction of low- and high-skilled workers work in a particular 2-digit industry or 2-digit occupation cell using the 1995 Intercensal Population Surveys (SUPAS), a nationally representative survey with data on a person's occupation and industry of employment. As an index for substitutability, we divide the fraction of high-skilled formal sector workers employed in a cell by the fraction of low-skilled formal sector workers employed in that cell. Thus, an index value of 1 would indicate that a given low-skilled worker was just as likely to be employed in that cell as a high-skilled worker.

We propose two potential classifications of "high-substitutability" cells: those where our index takes a value between 0.5 and 2 (so one type of worker is no more than twice as likely to be in the cell as the other type) and those where the index takes a value between 0.67 and 1.5 (so one type is no more than 50 % more likely to be in the cell than the other type). Figure 3 presents

[15] For example, if a district with a binding minimum wage is defined as being above the median in terms of the fraction of workers who earn within 20 - 30 % of the minimum wage, then between 26 - 32 % of districts change binding status in any given year; and only a minority of districts never change binding status.

the fraction of workers who belong to high-substitutability cells under either of these definitions. We find robust support for the idea that low- and high-skilled workers work in similar occupations and industries, particularly in the industries and occupations most affected by minimum wages. Overall, about 35 % (48 %) belong to an industry which is narrowly (broadly) characterised by a high degree of substitutability. When we focus on workers who earn within 30 % of the minimum wage, that number jumps to 60 % for the narrow measure and 80 % for the broad one. If we further examine urban areas only, to resemble our destination areas, that number becomes 87 % for the narrow measure and 95 % for the broad one. Similar numbers are obtained when using occupations rather than industries. We conclude that low- and high-skilled workers are broadly quite substitutable within Indonesia, and extremely substitutable in the jobs which are likely to be affected by a wage floor, again suggesting it is plausible that high-ability migrants could be displacing low-ability natives.

5 Robustness

In this section we perform various robustness checks to assess how sensitive our results are to changes in the specifications. Our necessary identification assumption is that local labour markets at the destination are not impacted by rainfall in the migration catchment area after controlling for the precipitation that the destination actually experiences. This assumption would be violated if, for example, increased incomes in the catchment area increase labour demand at the destination, perhaps due to trade. This would be a problem for our analysis if trade patterns are correlated with the migration patterns in the catchment area. First we will test this assumption by looking at the labour market impact of long-distance migration only. Then, we will test whether the migration patterns themselves appear relevant or if serial correlation within the catchment area would yield similar estimates for many correlated effects.

5.1 *Long-Distance Migration*

The exclusion restriction would be violated if rainfall at the origin affects labour market conditions at the destination via channels other than migration. This would happen if the areas are economically connected through the movements of goods rather of people. Specifically, good rainfall conditions at the origin could increase the supply and affordability of agricultural trade into urban areas, which could stimulate local labour markets. Table 10 tests this alternative channel by comparing our main results to those obtained when only considering migration that is at least 100 km in distance. After revealing a strong first stage relationship in column 2, columns 4 and 6 show that labour market effects are in fact larger for long-distance migration. The coefficient of column 4 shows that a one percentage point increase in the share of migrants reduces income by 2.37 %, compared to 0.92 % in our main specification, and that employment decreases by 0.65 instead of 0.22 percentage points.[16] Results are robust to alternative distance cut-offs (results not shown). The increased labour market impact of long-distance migration may result from differential sorting of distinct types of migration across distance.[17] If our results were driven by local trade, there would be no reason to believe that these effects would be stronger over longer distances.

5.2 *Serial Correlation Across the Catchment Area*

In our analysis so far, migration patterns showed up as a weighting on catchment area rainfall: origins for a potential destination received higher weight if a larger number of migrants came from this origin. If our exclusion restriction is invalid, and trade patterns (or any other relationship between destination labour markets and catchment area rainfall) are not coincident with migration patterns, we may expect different weighting schemes on catchment area rainfall to produce similar estimates. We test this hypothesis by bootstrapping precipitation weights. Our approach is as follows: for each destination, we fix the bootstrap catchment area to be the empirical migration catchment area we observe. We then bootstrap the weighted origin rainfall measure by drawing a set of weights for the districts within the catchment area from a uniform distribution.[18] If it is the case that our migration rainfall measure is simply proxying for some correlated activity that

[16] The migration rate is naturally lower for long-distance migration at 7.4 % compared to 15.9 %, so a one percentage point increase corresponds to a 13.5 % increase in the share of long-distance migrants.

[17] Using the same data source, Kleemans (2017) finds that those migrating over longer distances are positively selected in the sense that they are higher skilled and wealthier.

[18] We impose that the total catchment area weights sum to 1. This is necessary to preserve the magnitude of the independent variable. Since this normalization is necessary, it is not possible to preserve the distribution of underlying weights, which motivates this methodological choice.

takes place within the catchment area, we may expect many of these alternate weighting schemes to produce a similar relationship between catchment area rainfall, migration, and labour market outcomes.

Figure 4 demonstrates the F-statistic for migration responses to catchment area rainfall using 10,000 bootstrapped weights. While the empirical F-statistic using actual migration patterns shown in Table 2 equals 22.76, the largest of the 10,000 bootstrapped F-statistics is under 3. In other words, while migration patterns are strongly related to rainfall at the origins weighted by the places that migrants actually come from, it is not strongly related to rainfall at alternate weighting schemes within the catchment area. The migration weights seem critical for migration patterns, which is reassuring. Figure 5 presents the reduced-form coefficients from destination wages on catchment area rainfall. When using the actual migration weights, this coefficient is 0.059. The distribution of coefficients using the bootstrapped weights is nearly always small and positive, suggesting that any effects of local rainfall within the catchment area are positive. However, in 10,000 bootstrapped replications, they are never as large as the coefficient using actual migration patterns.

From this analysis, we infer that the correlation between origin area rainfall and destination labour market effects are largest for the parts of the catchment area which send the most migrants to the destination in response to rainfall shocks. This analysis rules out the possibility that destination labour markets are affected by origin-area rainfall if these labour market effects follow a different pattern than migration.

5.3 *Alternative Origin Area Weights*

The first stage analysis uses weights w_o according to equation (1) to indicate the relative importance of an origin area to the destination area under consideration. For each destination, the weights are calculated by dividing the number of migrants from a certain origin area o who reside at destination area d, by all migrants at destination area d. Weights are fixed over time and are calculated using migration patterns during the 13 years preceding our panel from 1975 to 1987. We perform two robustness checks. First, we calculate weights using the 13 years during our panel from 1988 to 2000. This likely reduces measurement error in the observed migration patterns but it introduces the potential endogeneity concern that the weights are mechanically related to the migrant stock variable. Nonetheless, we show the main results in Appendix Tables A5 and A6 and these are consistent with Tables 5 and 7, which is reassuring. In a second robustness check, we calculate weights using auxiliary data from the Intercensal Population Surveys (SUPAS), which is carried out in the mid-period between two population censuses. We use the 1985 SUPAS which was completed just before the start of our panel in 1988, and that reports the current and birth location of 605,858 individuals. The sampling frame of the SUPAS is unfortunately different from that of the IFLS and as a result only 74 % of locations can be matched. While this reduces power, we nonetheless show in Table A7 that the second stage results are consistent with our main findings in Table 5.

5.4 *Alternative Weather Measures*

So far, the analyses have used precipitation z-score as weather variable and have thereby implicitly assumed a linear relation between rainfall z-scores and economic outcomes. Robustness checks show that results are robust to using precipitation levels, deviations from the mean, adding squared precipitation, and adding temperature (results not shown). If dummy variables are used for extreme weather events like droughts and floods, the results become less precise but are still broadly consistent with the findings of this paper. One concern is the possibility that a few extreme weather events play a strong role in inference. In particular, Indonesia was impacted by an extreme drought which was coincident with the financial crisis of 1997. To ensure that extreme weather events in this year are not driving the results, we repeated all analyses excluding 1997 from the sample and excluding 1997 and 1998. The results remain broadly unchanged and increases slightly in magnitude.[19]

5.5 *Alternative Sample Definitions and Clustering*

All main analyses are carried out at the individual-level allowing us to incorporate individual-level control variables. Appendix Table A8 shows the main reduced form and second stage results when the data are collapsed to the destination level. Given that standard errors are clustered at the

[19] When excluding 1997, a one percentage point increase in the share of migrants decreases income by 1.04 % (s.e. 0.557) and reduces employment by 0.33 percentage points (s.e. 0.164). When excluding 1997 and 1998, income reduces by 1.60 % (s.e. 0.689) and employment decreases 0.43 percentage point (s.e. 0.197).

destination level in both cases, the results are similar.

Since rainfall shocks across the catchment area are used in calculating the independent variable of interest, it would be desirable to use a Conley (1999) cluster to allow for correlations across the catchment area. This correction becomes computationally infeasible on our full dataset with 192,237 observations at the individual-year level. To test whether the potential correlations in the instrument could be biasing our standard error estimates, we therefore reran the primary analysis at the destination level using the Conley errors. The main second stage results are available in columns 5 and 6 of Appendix Table A8. This approach demonstrates that the Conley errors are smaller than the destination clustered errors, suggesting that p-values presented in this paper are conservative.

Additional robustness checks have been carried out which alternative sample definitions, none of which significantly affect the results. Several districts in our sample were not part of the original IFLS sample, but were added as respondents were tracked over time. The results do not change when we only use the original IFLS sample. Some of the new districts only host a few IFLS respondents in a given year. When leaving out districts with less than 3 respondents in a year, the results do not change either.

6 Conclusion

This paper employs an instrumental variable approach to study the labour market response to immigration in Indonesia. Exogenous variation in the number of immigrants arriving at a destination is obtained from rainfall shocks at their areas of origin. This paper finds a strong and robust first stage relationship, indicating that people are more likely to leave areas after experiencing a bad weather shock. The second stage confirms predictions from economic theory that increased immigration tends to lower income and employment. Point estimates from this study indicate that a one percentage point increase in the share of migrants at the destination decreases average income per hour by 0.97 % and reduces the number of people employed by 0.24 percentage points. The analysis shows that the negative income effects are concentrated in the informal sector with a 1.84 % decrease in informal sector income, while employment effects are strongest in the formal sector at 0.33 percentage point, both following a one percentage point increase in the migrant share. These effects are what we would expect in Indonesia's two-sector labour market, as employment is the primary mechanism for adjustment in the heavily-regulated formal sector, while wages should adjust in the more competitive informal sector.

Exploring heterogeneous labour market effects reveals that the negative consequences are not evenly distributed across subgroups of the population, but are most pronounced for low-skilled individuals. Previous studies have attributed disproportional negative impacts on low-skilled natives to a high degree of substitutability with incoming migrants. This argument does not hold for our sample, as migrants have higher levels of education than natives. In Section 4, we find little evidence that this result could be explained by differences in the returns to skill for migrants or by distinctions in migrant characteristics among LATE compliers. Instead we suggest that this result may be understood as another consequence of the two-sector labour market with a wage floor in the formal sector where the disadvantaged group faces changes of disemployment or employment to the informal sector. Short of a conclusive test for this explanation, we suggest that a fruitful avenue for further research is a continued investigation of whether migration more adversely affects similar natives or the most disadvantaged individuals in developing country labour markets.

Finally, it is important to note that this paper considers short-term impacts only. If labour demand can be approximated to be fixed in the short run, then increased labour supply will drive down wages and employment. In the long run, however, labour markets may adjust to the migration-induced increase of labour by expanding production or adjusting the production input mix, which may mitigate or even cancel out short-term economic losses. Without a suitable long-run migration instrument, we can only speculate as to these dynamic patterns.

University of Illinois at Urbana-Champaign

University of California at Berkeley

References

Alatas, V. and Cameron, L.A. (2008). 'The impact of minimum wages on employment in a low-income country: a quasi-natural experiment in Indonesia', *Industrial and Labor Relations Review*, vol. 61(2), pp. 201–23.

Bazzi, S. (2016). 'Wealth heterogeneity and the income elasticity of migration', *American Economic Journal: Applied Economics*, Forthcoming.

Bell, M. and Charles-Edwards, E. (2013). 'Cross-national comparisons of internal migration: an update on global patterns and trends', United Nations Department of Economic and Social Affairs.

Borjas, G.J. (2003). 'The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market', *Quarterly Journal of Economics*, vol. 118(4), pp. 1335–74.

Boustan, L.P., Fishback, P.V. and Kantor, S. (2010). 'The effect of internal migration on local labor markets: American cities during the Great Depression', *Journal of Labor Economics*, vol. 28(4), pp. 719–46.

Bryant, J. and Rukumnuaykit, P. (2007). 'Labor migration in the greater Mekong sub-region: does immigration to Thailand reduce the wages of Thai workers?', Washington DC: World Bank.

Card, D. and Lemieux, T. (2001). 'Can falling supply explain the rising return to college for younger men? A cohort-based analysis', *Quarterly Journal of Economics*, vol. 116(2), pp. 705–46.

Conley, T.G. (1999). 'GMM estimation with cross sectional dependence', *Journal of Econometrics*, vol. 92(1), pp. 1–45.

Deb, P. and Seck, P. (2009). 'Internal migration, selection bias and human development: evidence from Indonesia and Mexico', Human Development Report Office (HDRO), United Nations Development Programme (UNDP).

Harris, J.R. and Todaro, M.P. (1970). 'Migration, unemployment & development: a two-sector analysis', *American Economic Review*, vol. 60(1), pp. 126–42.

IMF (2017). 'International financial statistics', Washington DC: International Monetary Fund.

Kerr, S.P. and Kerr, W.R. (2011). 'Economic impacts of immigration: a survey', *Finnish Economic Papers*, vol. 24(1), pp. 1–32.

Kishore, K., Subbiah, A.R., Sribimawati, T., Diharto, S., Alimoeso, S., Rogers, P. and Setiana, A. (2000). 'Indonesia country study.', Asian Disaster Preparedness Center.

Kleemans, M. (2017). 'Migration choice under risk and liquidity constraints', Working Paper, University of Illinois at Urbana-Champaign.

Kleemans, M. and Klugman, J. (2009). 'Understanding attitudes towards migrants: a broader perspective', United Nations Development Programme (UNDP), Human Development Research Paper 2009/53.

Levine, D.I. and Yang, D. (2014). 'The impact of rainfall on rice output in Indonesia', NBER Working Paper No.20302, University of California, Berkeley and University of Michigan at Ann Arbor.

Maccini, S.L. and Yang, D. (2009). 'Under the weather: health, schooling, and economic consequences of early-life rainfall', *American Economic Review*, vol. 99(3), pp. 1006–26.

Magruder, J.R. (2013). 'Can minimum wages cause a big push? Evidence from Indonesia', *Journal of Development Economics*, vol. 100(1), pp. 48–62.

Matsuura, K. and Willmott, C.J. (2009). 'Terrestrial air temperature and precipitation: monthly climatologies', Center for Climatic Research, Department of Geography, University of Delaware.

McKenzie, D., Theoharides, C. and Yang, D. (2014). 'Distortions in the international migrant labor market: evidence from Filipino migration and wage responses to destination country economic shocks', *American Economic Journal: Applied Economics*, vol. 6(2), pp. 49–75.

Munshi, K. (2003). 'Networks in the modern economy: Mexican migrants in the U.S. labor market', *Quarterly Journal of Economics*, vol. 118(2), pp. 549–99.

Okkerse, L. (2008). 'How to measure labour market effects of immigration: a review', *Journal of Economic Surveys*, vol. 22(1), pp. 1–30.

Stock, J.H. and Yogo, M. (2005). 'Testing for weak instruments in linear IV regression', in (D. W. K. Andrews and J. H. Stock, eds.), *Identification and Inference for Econometric Models*, pp. 80–108, Cambridge University Press.

Strauss, J., Beegle, K., Sikoki, B., Dwiyanto, A., Herawati, Y. and Witoelar, F. (2004). 'The third wave of the Indonesia family life survey (IFLS): overview and field report', *WR-144/1-NIA/NICHD*.

Strobl, E. and Valfort, M.A. (2015). 'The effect of weather-induced internal migration on local labor markets. Evidence from Uganda', *World Bank Economic Review*, vol. 29(2), pp. 385–412.

UNDESA (2013). 'International migration report 2013', Population Division, Department of Economic and Social Affairs, United Nations, (ST/ESA/SER.A/384).

UNDP (2009). *HDR 2009 - Overcoming barriers: Human mobility and development*, no. hdr2009 in Human Development Report (1990 to present), Human Development Report Office (HDRO), United Nations Development Programme (UNDP).

Tables and Figures

Table 1: *Summary Statistics*

	All	Natives	Migrants	t-statistic of mean comparison test
Number of individuals	28,766			
Migrant stock at destination (%)	15.8 (17.7)			
Precipitation (mm per month)	170.2 (47.9)			
Male (%)	51.8 (50.0)	51.3 (50.0)	53.6 (49.9)	-8.4
Education level	1.45 (1.21)	1.34 (1.17)	1.81 (1.28)	-73.2
Highly-educated dummy (%)	38.4 (48.6)	34.6 (47.6)	51.0 (50.0)	-62.6
Age	37.0 (15.1)	37.1 (15.5)	36.7 (13.8)	4.4
Log hourly income (Rp)	7.61 (1.13)	7.53 (1.13)	7.88 (1.10)	-48.4
Log hourly income formal sector (Rp)	7.75 (1.06)	7.66 (1.06)	8.00 (1.02)	-38.9
Log hourly income informal sector (Rp)	7.59 (1.24)	7.53 (1.23)	7.84 (1.24)	-27.3
Employment rate (%)	78.7 (40.9)	78.7 (41.0)	78.9 (40.8)	-1.0
Formal employment rate (%)	39.7 (48.9)	37.5 (48.4)	47.5 (49.9)	-38.0
Informal employment rate (%)	51.9 (50.0)	54.3 (49.8)	43.6 (49.6)	39.4
Hours per week	37.1 (21.5)	35.9 (21.5)	40.9 (21.0)	-38.2
Number of individual-year pairs	192,237	148,565	43,672	

Dataset consists of individual-year observations, each of which is counted seperately, based on the information of 28,766 individuals who may change migrant status over time. Mean is shown with standard deviation between brackets. Values for education level are: 0 = no education, 1 = primary school, 2 = junior high school, 3 = senior high school, 4 = university. A person is classified as highly-educated if he or she has at least some high school education (education level 2 or higher). Log income per hour is measured in Indonesian Rupiah and employment rate is the percentage of individuals employed. All employment is included and some individuals have a job in the formal sector as well as a job in the informal sector.

Table 2: *Migrants' Responsiveness to Weather Shocks (First Stage)*

	Dependent variable: Migrant Share of the Population					
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation lead						-0.010
						[0.010]
Precipitation	-0.045***		-0.033***		-0.037***	
	[0.013]		[0.011]		[0.011]	
Precipitation lagged		-0.066***	-0.059***	-0.062***	-0.054***	
		[0.014]	[0.012]	[0.013]	[0.011]	
Precipitation lagged twice				-0.021***	-0.025***	
				[0.006]	[0.006]	
Precipitation at destination lead						-0.001
						[0.008]
Precipitation at destination	0.035***		0.026***		0.029***	
	[0.012]		[0.010]		[0.010]	
Precipitation at destination lagged		0.049***	0.043***	0.045***	0.038***	
		[0.012]	[0.011]	[0.012]	[0.010]	
Precipitation at destination lagged twice				0.021***	0.024***	
				[0.005]	[0.005]	
F statistic of joint significance	**11.64**	**22.76**	**12.14**	**12.23**	**8.60**	**0.99**
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes	yes	yes
R-squared	0.29	0.31	0.31	0.31	0.32	0.28
Observations	148,565	148,565	148,565	148,565	148,565	148,565
Number of destinations	205	205	205	205	205	205

All regressions use individual-level data and standard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. Unless noted otherwise, precipitation variables refer to origin area precipitation z-scores and are summed over the entire catchment area of each destination according to equation (1). Socio-economic control variables include dummies variables for gender, education level and age group.

Table 3: *Rainfall and Labour Market Effects (Reduced Form)*

	Dependent variable:	
	Log income per hour	**Employment**
	(1)	(2)
Precipitation lagged	0.059**	0.016**
	[0.026]	[0.008]
Precipitation at destination lagged	-0.010	-0.019***
	[0.015]	[0.005]
Time fixed effects	yes	yes
Destination fixed effects	yes	yes
Socio-Economic control variables	yes	yes
R-squared	0.12	0.19
Observations	100,612	148,300
Number of destinations	205	205

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. Unless noted otherwise, precipitation variables refer to origin area precipitation z-scores and are summed over the entire catchment area of each destination according to equation (1). Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table 4: *Labour Market Response to Immigration (Second Stage)*

	Dependent variable:			
	Log income per hour		**Employment**	
	OLS	IV-2SLS	OLS	IV-2SLS
	(1)	(2)	(3)	(4)
Migrant share predicted from the first stage	0.02	-0.97**	-0.03	-0.24**
	[0.091]	[0.474]	[0.026]	[0.122]
Precipitation destination lagged	0.03**	0.03**	-0.01***	-0.01**
	[0.011]	[0.014]	[0.003]	[0.004]
F statistic of first stage relationship		22.76		22.71
Time fixed effects	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes
R-squared	0.12	0.12	0.19	0.19
Observations	100,612	100,611	148,300	148,300
Number of destinations	205	204	205	205

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. (1) and (3) use OLS; (2) and (4) use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table 5: *Labour Market Response in Formal and Informal Sector*

Panel A. Dependent variable: Log income per hour

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.97**	-0.28	-1.84**
	[0.475]	[0.387]	[0.793]
Precipitation destination lagged	0.03**	0.02	0.04**
	[0.014]	[0.014]	[0.020]
F statistic of first stage relationship	22.67	21.84	21.76
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.12	0.13	0.09
Observations	100,545	54,008	61,150
Number of destinations	190	190	190

Panel B. Dependent variable: Employment

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.24*	-0.33***	-0.08
	[0.122]	[0.109]	[0.122]
Precipitation destination lagged	-0.01**	0.00	-0.01
	[0.004]	[0.004]	[0.005]
F statistic of first stage relationship	22.65	22.64	22.64
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.19	0.10	0.12
Observations	148,188	148,161	148,161
Number of destinations	190	190	190

All regressions use individual-level data and standard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is slightly smaller than in Table 4 in order to ensure that all destinations have sufficient observations across sectors. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table 6: *Labour Market Response in Formal and Informal Sector with Individual Fixed Effects*

Panel A. Dependent variable: Log income per hour

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-1.11**	-0.11	-2.22**
	[0.532]	[0.352]	[0.902]
Precipitation z-scores at destination lagged	0.03**	0.01	0.03**
	[0.013]	[0.010]	[0.017]
F statistic of first stage relationship	22.05	20.13	23.09
Time fixed effects	yes	yes	yes
Individual fixed effects	yes	yes	yes
Socio-Economic control variables	no	no	no
R-squared	0.05	0.07	0.04
Observations	98,929	52,438	60,306
Number of individuals	14,415	8,938	8,577

Panel B. Dependent variable: Employment

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.14	-0.23**	-0.05
	[0.115]	[0.107]	[0.109]
Precipitation z-scores at destination lagged	-0.01***	-0.00	-0.01**
	[0.003]	[0.003]	[0.004]
F statistic of first stage relationship	21.33	21.29	21.29
Time fixed effects	yes	yes	yes
Individual fixed effects	yes	yes	yes
Socio-Economic control variables	no	no	no
R-squared	0.02	0.01	0.01
Observations	144,635	144,606	144,606
Number of individuals	20,555	20,553	20,553

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. All regressions include individual fixed effects and no socio-economic control variables are included.

Table 7: *Heterogeneous Labour Market Impacts by Sector*

Panel A. Dependent variable: Log income per hour	All		Formal sector		Informal sector	
	Low Education	High Education	Low Education	High Education	Low Education	High Education
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share predicted from the first stage	-1.90**	-0.28	-0.92	-0.11	-2.47***	-1.34
	[0.801]	[0.389]	[0.881]	[0.333]	[0.949]	[0.963]
Precipitation destination lagged	0.03*	0.02	0.01	0.01	0.03	0.06*
	[0.016]	[0.019]	[0.018]	[0.018]	[0.020]	[0.036]
F statistic of first stage relationship	18.90	23.79	14.24	24.23	17.99	23.24
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes	yes	yes
R-squared	0.06	0.15	0.06	0.18	0.04	0.09
Observations	67,368	31,902	31,292	22,191	46,081	14,186
Number of destinations	173	173	171	172	173	173

Panel B. Dependent variable: Employment	All		Formal sector		Informal sector	
	Low Education	High Education	Low Education	High Education	Low Education	High Education
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share predicted from the first stage	-0.34	-0.05	-0.32*	-0.19	-0.23	0.07
	[0.225]	[0.129]	[0.182]	[0.142]	[0.199]	[0.136]
Precipitation destination lagged	-0.01***	-0.00	-0.00	-0.00	-0.01	-0.01
	[0.004]	[0.006]	[0.005]	[0.006]	[0.005]	[0.008]
F statistic of first stage relationship	17.11	24.27	17.09	24.30	17.09	24.30
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes	yes	yes
R-squared	0.13	0.26	0.09	0.15	0.09	0.09
Observations	95,523	50,529	95,508	50,517	95,508	50,517
Number of destinations	173	173	173	173	173	173

All regressions use individual-level data and standard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. Low-skilled individuals are defined as those with no or only primary education and high-skilled individuals are those with at least some secondary education. The number of observations is smaller than in Table 5 in order to ensure that all destinations have sufficient low- and high-skilled individuals in each sector. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table 8: *Mincer Regressions*

	Dependent variable: Log income per hour					
	(1) **All**	(2) **Natives**	(3) **Migrants**	(4) **All**	(5) **Natives**	(6) **Migrants**
Education level	0.297***	0.282***	0.317***			
	[0.009]	[0.011]	[0.014]			
Years of education				0.078***	0.073***	0.087***
				[0.002]	[0.003]	[0.004]
Male	0.274***	0.288***	0.228***	0.267***	0.286***	0.208***
	[0.019]	[0.024]	[0.028]	[0.020]	[0.024]	[0.027]
Age	0.045***	0.040***	0.064***	0.047***	0.041***	0.064***
	[0.003]	[0.003]	[0.006]	[0.003]	[0.003]	[0.006]
Age squared	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.14	0.12	0.19	0.14	0.12	0.19
Observations	131,908	100,612	31,296	131,864	100,584	31,280
Number of destinations	205	205	200	205	205	200

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. Log income per hour is measured in Indonesian Rupiah and education values stand for: 0 = no education, 1 = primary school, 2 = junior high school, 3 = senior high school, 4 = university.

Table 9: *Quantifying the Local Average Treatment Effect*

	Sample: Those who arrived at a destination as a migrant Dependent variable: Being highly-educated				
	(1)	(2)	(3)	(4)	(5)
Precipitation		0.036	0.034		0.049*
		[0.025]	[0.026]		[0.026]
Precipitation lagged	0.016		0.010	0.003	-0.011
	[0.035]		[0.035]	[0.033]	[0.034]
Precipitation lagged twice				0.040	0.053*
				[0.029]	[0.030]
Time fixed effects	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes
R-squared	0.02	0.02	0.02	0.02	0.02
Observations	3,856	3,856	3,856	3,856	3,856
Number of destinations	198	198	198	198	198

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. Precipitation variables refer to origin area precipitation z-scores and are summed over the entire catchment area of each destination according to equation (1).

Table 10: *Long Distance Migration*

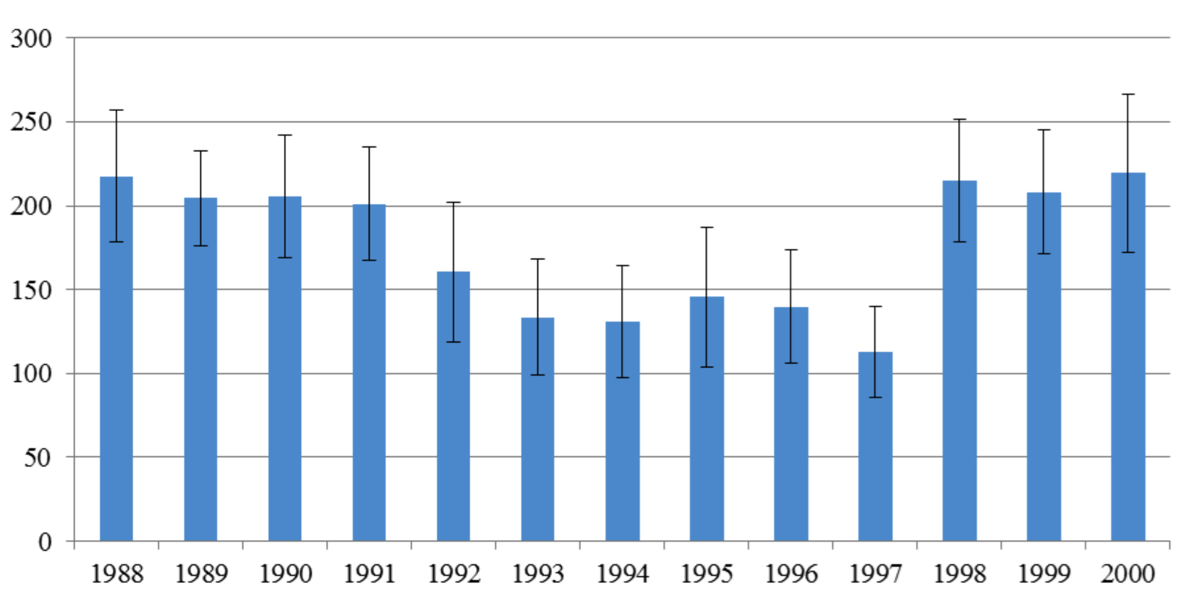
	Migrants' responsiveness to weather shocks		Labor market response to immigration			
Dependent variable:	**Migrant share**		**Log income per hour**		**Employment**	
	All migration	**Migration > 100 km**	**All migration**	**Migration > 100 km**	**All migration**	**Migration > 100 km**
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation lagged	-0.066***	-0.020***				
	[0.014]	[0.005]				
Migrant share predicted from the first stage			-0.92*	-2.37**	-0.22*	-0.65**
			[0.473]	[1.147]	[0.120]	[0.297]
Precipitation at destination lagged	0.049***	0.018***	0.03**	0.05**	-0.01**	-0.00
	[0.012]	[0.005]	[0.014]	[0.020]	[0.004]	[0.005]
Mean dependent variable	15.9%	7.4%	7.53	7.53	78.7%	78.7%
F statistic of first stage relationship	22.55	17.95	22.54	21.27	22.50	17.93
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes	yes	yes
R-squared	0.31	0.20	0.12	0.11	0.19	0.19
Observations	147,098	147,098	99,632	99,632	146,835	146,835
Number of destinations	198	198	197	197	198	198

All regressions use individual-level data and standard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. Unless noted otherwise, precipitation variables refer to origin area precipitation z-scores and are summed over the entire catchment area of each destination according to equation (1). Columns (2), (4) and (6) only consider migration over at least 100 km distance. Columns (3), (4), (5) and (6) use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Figure 1: *Individual Locations and Weather Data*

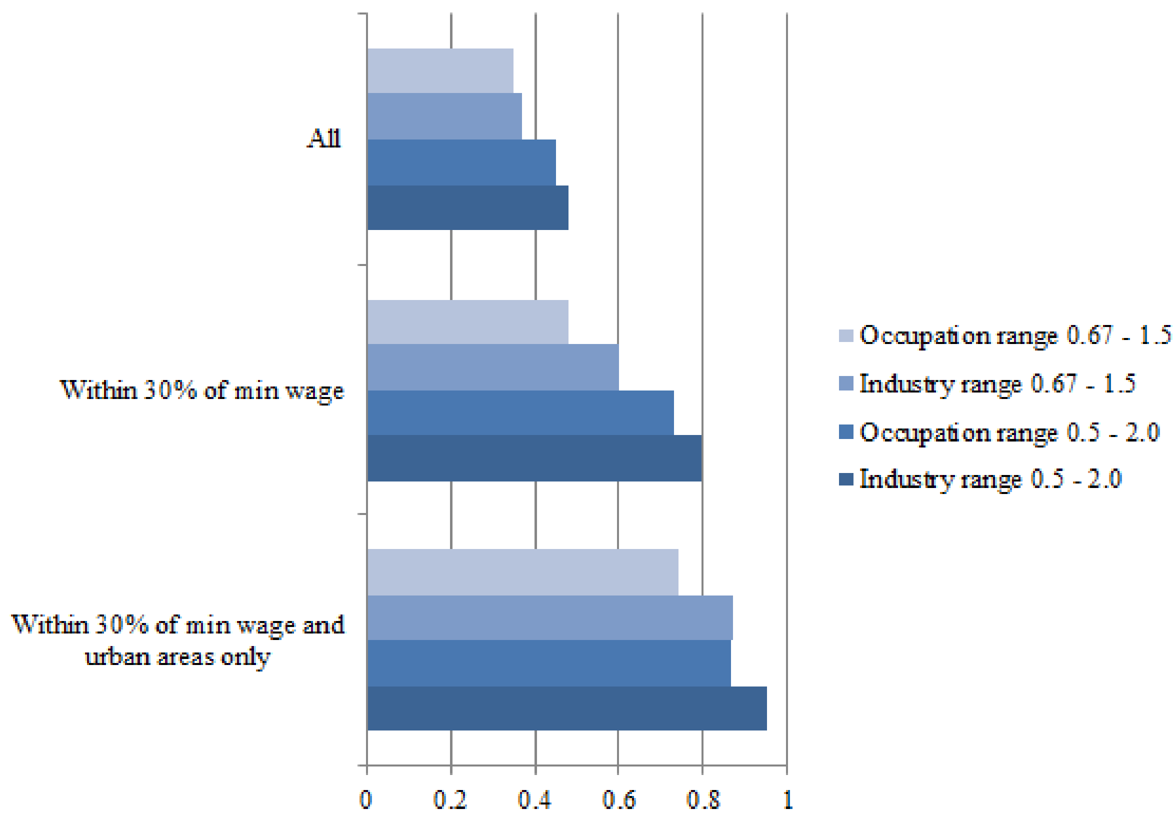
Individual locations from the Indonesia Family Life Survey (red dots) with weather data that the locations are mapped to (blue squares). Weather data are obtained from the Center for Climatic Research of the University of Delaware (Matsuura and Willmott, 2009).

Figure 2: *Precipitation (mm per month)*



Average precipitation in millimeter per month during the study period. Weather data are obtained from the Center for Climatic Research of the University of Delaware (Matsuura and Willmott, 2009).

Figure 3: *Share of Workers in Jobs with High Substitutability between Low- and High-Skilled Workers*



The index for substitutability is calculated by dividing the share of high-skilled formal sector workers who are employed in a 2-digit industry or occupation cell by the share of low-skilled formal sector workers who are employed in that cell. A value of 1 indicates that low-skilled workers are just as likely to work in that cell as high-skilled workers are. This figure shows the share of industry or occupation cells with values within the 0.67 - 1.5 or the 0.5 - 2 range of the index of substitutability.

Figure 4: *Bootstrapped First Stage F-Statistics using Random Rainfall Weights*

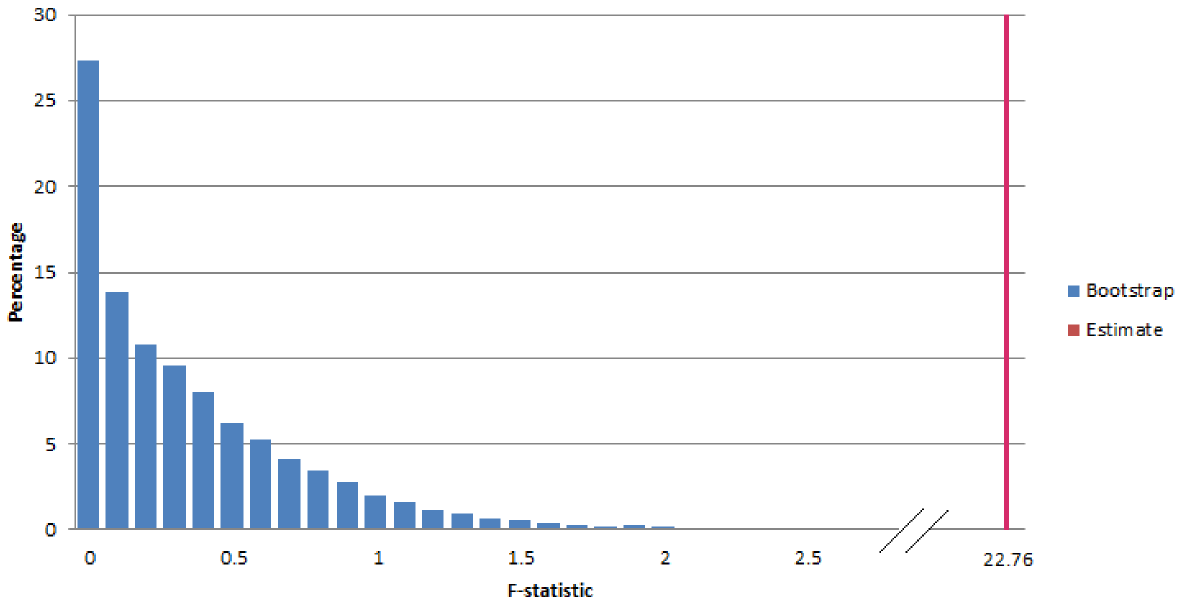
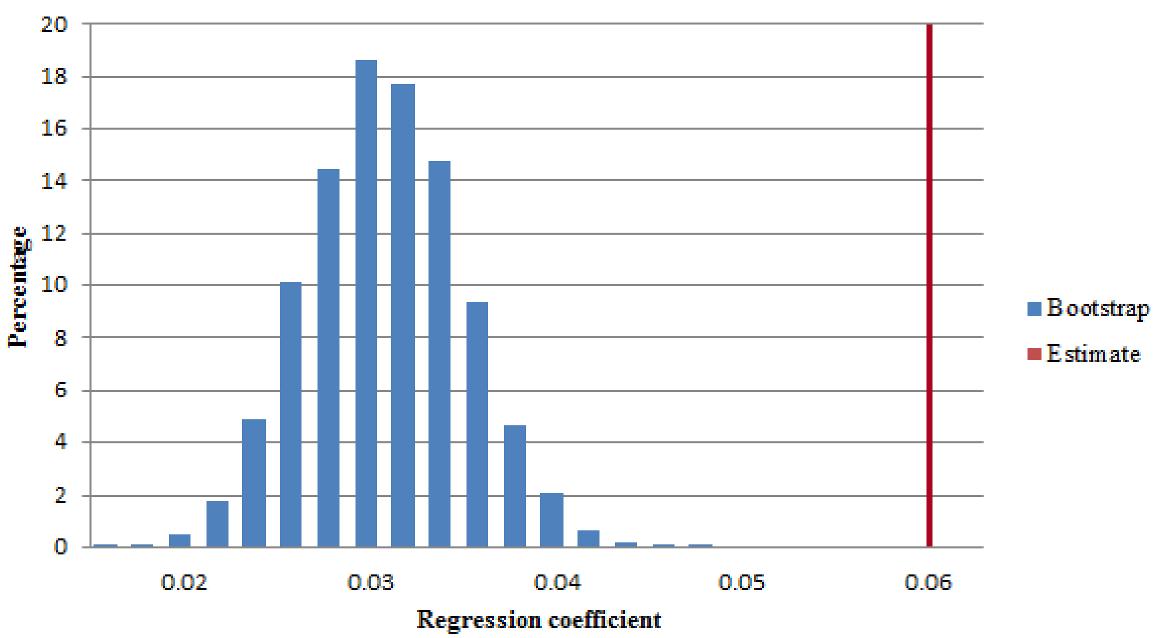


Figure 5: *Bootstrapped Reduced-Form Coefficients using Random Rainfall Weights*



Appendix A

Proof of Statement 1 (Page 16):

$$\frac{\partial w_j}{\partial L_j} < 0$$

$$\frac{\partial w_j}{\partial L_j} = \alpha(\alpha-\nu)\theta_j^2 K^{1-\alpha} L_j^{2\nu-2}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-2\nu)/\nu} - (1-\nu)\alpha\theta_j K^{1-\alpha} L_j^{\nu-2}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu} < 0$$

$$(\alpha-\nu)(\theta_j L_j^{\nu}) < (1-\nu)\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)$$

We know that $0 < \alpha < 1$ so it must be the case that $\alpha - \nu < 1 - \nu$.

Furthermore, we know that $(\theta_j L_j^{\nu}) < (\sum_{k=1}^{n}\theta_k L_k^{\nu})$. Therefore, we can conclude $\frac{\partial w_j}{\partial L_j} < 0$

Proof of Statement 2 (Page 16):

$$\frac{\partial w_j}{\partial L_g} < 0$$

Note that terms are positive except $(\alpha-\nu)$, which is negative for $\alpha < \nu$. Hence it follows that if $\alpha < \nu \Rightarrow \partial w_g/\partial L_g < 0$.

Proof of Statement 3 (Page 16):

$$\frac{\partial w_j}{\partial L_j} < \frac{\partial w_j}{\partial L_g}$$

$$\alpha(\alpha-\nu)\theta_j^2 K^{1-\alpha} L_j^{2\nu-2}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-2\nu)/\nu} - (1-\nu)\alpha\theta_j K^{1-\alpha} L_j^{\nu-2}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu}$$

$$< \frac{\alpha(\alpha-\nu)\theta_j\theta_g K^{1-\alpha}}{L_j^{1-\nu}L_g^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-2\nu)/\nu}$$

$$(\alpha-\nu)(\theta_j L_j^{\nu} - \theta_g L_j L_g^{\nu-1}) < (1-\nu)\sum_{k=1}^{n}\theta_k L_k^{\nu}$$

We know that $(\theta_j L_j^{\nu} - \theta_g L_j L_g^{\nu-1}) < \theta_j L_j^{\nu} < \sum_{k=1}^{n}\theta_k L_k^{\nu}$ and we also showed earlier that $(\alpha-\nu) < (1-\nu)$ so the inequality holds.

Derivation of conditions under which $\partial\bar{w}_g/\partial L_j < \partial w_j/\partial L_j$ in the two-sector model (page 19):

The cross derivative is

$$\bar{w}_g = \frac{L_I^{\gamma-1}(L_g - \hat{L}_g) + \hat{w}\hat{L}_g}{L_g}$$

Define $I = L_I^{\gamma-1}$. Then

$$\frac{\partial\bar{w}_g}{\partial L_j} = \frac{\hat{w} - I}{L_g}\frac{\partial\hat{L}_g}{\partial L_j} + \frac{L_g - \hat{L}_g}{L_g}(\gamma-1)L_I^{\gamma-2}\frac{\partial L_I}{\partial L_j}$$

where

$$\hat{L}_g = \left[\frac{\alpha\theta_g K^{1-\alpha}}{\hat{w}}\right]^{\frac{1}{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{\frac{(\alpha-\nu)}{\nu(1-\nu)}}$$

since

$$\frac{\partial\hat{L}_{g'}}{\partial L_j} = \left[\frac{\alpha\theta_{g'} K^{1-\alpha}}{\hat{w}}\right]^{\frac{1}{1-\nu}}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\theta_j}{L_j^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{\frac{\alpha-\nu-\nu(1-\nu)}{\nu(1-\nu)}} \quad \forall g'$$

And all components are necessarily positive save $\alpha-\nu$, we have immediately that $\frac{\partial\hat{L}_{g'}}{\partial L_j}$ has the same sign as $\alpha-\nu$

Moreover, since

$$\frac{\partial L_I}{\partial L_j} = -\sum_{g'}\frac{\partial\hat{L}_{g'}}{\partial L_j}$$

We have $\alpha < \nu \Rightarrow \frac{\partial L_I}{\partial L_j} > 0$. Define

$$\xi_j^I = \frac{(L_g - \hat{L}_g)}{L_g}(\gamma-1)L_I^{\gamma-2}\frac{\partial L_I}{\partial L_j}$$

which has the opposite sign from $\frac{\partial L_I}{\partial L_j}$.

Now, note that

$$\frac{\partial \bar{w}_g}{\partial L_j} = \frac{\hat{w} - I}{L_g}\frac{\partial \hat{L}_g}{\partial L_j} + \frac{L_g - \hat{L}_g}{L_g}(\gamma - 1)L_I^{\gamma-2}\frac{\partial L_I}{\partial L_j}$$

$$= \frac{\hat{w} - I}{L_g}\left[\frac{\alpha\theta_g K^{1-\alpha}}{\hat{w}}\right]^{\frac{1}{1-\nu}}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\theta_j}{L_j^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{\frac{\alpha-\nu-\nu(1-\nu)}{\nu(1-\nu)}} + \xi_j^I$$

We will now derive a bound for the conditions under which

$$\frac{\partial \bar{w}_g}{\partial L_j} < \frac{\partial w_j}{\partial L_j}$$

$$\frac{\hat{w} - I}{L_g}\left[\frac{\alpha\theta_g K^{1-\alpha}}{\hat{w}}\right]^{\frac{1}{1-\nu}}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\theta_j}{L_j^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{\frac{\alpha-\nu-\nu(1-\nu)}{\nu(1-\nu)}} + \xi_j^I$$

$$< \alpha(\alpha-\nu)\theta_j^2 K^{1-\alpha}L_j^{2\nu-2}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-2\nu)/\nu}$$

$$-(1-\nu)\alpha\theta_j K^{1-\alpha}L_j^{\nu-2}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu}$$

Recall that

$$w_j = \alpha\theta_j K^{1-\alpha}L_j^{\nu-1}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu}$$

We need to show that

$$\frac{\hat{w} - I}{L_g}\left[\frac{\alpha\theta_g K^{1-\alpha}}{\hat{w}}\right]^{\frac{1}{1-\nu}}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\theta_j}{L_j^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{\frac{\alpha-\nu-\nu(1-\nu)}{\nu(1-\nu)}} + \xi_j^I < w_j\left[\frac{(\alpha-\nu)\theta_j}{L_j^{1-\nu}\sum_{k=1}^{n}\theta_k L_k^{\nu}} - \frac{1-\nu}{L_j}\right]$$

As shown earlier

$$\hat{w} = \frac{\alpha\theta_g K^{1-\alpha}}{\hat{L}_g^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu}$$

so that

$$\hat{w}^{1/(1-\nu)}\hat{L}_g = (\alpha\theta_g K^{1-\alpha})^{1/(1-\nu)}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{(\alpha-\nu)/\nu(1-\nu)}$$

Substituting this in gives

$$\frac{\hat{w}-I}{L_g}\left[\frac{\alpha\theta_g K^{1-\alpha}}{\hat{w}}\right]^{\frac{1}{1-\nu}}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\theta_j}{L_j^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{\frac{\alpha-\nu-\nu(1-\nu)}{\nu(1-\nu)}}+\xi_j^I<\frac{w_j}{L_j}\left[\frac{(\alpha-\nu)\theta_j L_j^{\nu}}{\sum_{k=1}^{n}\theta_k L_k^{\nu}}-(1-\nu)\right]$$

$$\frac{\hat{w}-I}{L_g}\left[\frac{1}{\hat{w}}\right]^{1/(1-\nu)}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\theta_j}{L_j^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{-1}\hat{L}_g\hat{w}^{1/(1-\nu)}+\xi_j^I<\frac{w_j}{L_j}\left[\frac{(\alpha-\nu)\theta_j L_j^{\nu}}{\sum_{k=1}^{n}\theta_k L_k^{\nu}}-(1-\nu)\right]$$

$$\frac{\hat{w}-I}{L_g}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\theta_j}{L_j^{1-\nu}}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{-1}\hat{L}_g+\xi_j^I<\frac{w_j}{L_j}\left[\frac{(\alpha-\nu)\theta_j L_j^{\nu}}{\sum_{k=1}^{n}\theta_k L_k^{\nu}}-(1-\nu)\right]$$

$$\frac{\hat{w}-I}{L_g}\left(\frac{\alpha-\nu}{1-\nu}\right)\theta_j L_j^{\nu}\left(\sum_{k=1}^{n}\theta_k L_k^{\nu}\right)^{-1}\hat{L}_g+L_j\xi_j^I<w_j\left[\frac{(\alpha-\nu)\theta_j L_j^{\nu}}{\sum_{k=1}^{n}\theta_k L_k^{\nu}}-(1-\nu)\right]$$

The inequality holds if

$$w_j(1-\nu)<w_j\frac{(\alpha-\nu)\theta_j L_j^{\nu}}{\sum_{k=1}^{n}\theta_k L_k^{\nu}}-\frac{\hat{w}-I}{L_g}\left(\frac{\alpha-\nu}{1-\nu}\right)\frac{\hat{L}_g L_j^{\nu}\theta_j}{(\sum_{k=1}^{n}\theta_k L_k^{\nu})}-L_j\xi_j^I$$

or if

$$w_j(1-\nu)<\frac{(\alpha-\nu)\theta_j L_j^{\nu}}{\sum_{k=1}^{n}\theta_k L_k^{\nu}}\left[w_j-\left(\frac{\hat{w}-I}{1-\nu}\right)\frac{\hat{L}_g}{L_g}\right]-L_j\xi_j^I$$

$\gamma=1\Rightarrow\xi_j^I=0$ and $\gamma<1\Rightarrow\xi_j^I<0$ which gives the result in the paper.

Appendix B

Table A1: *Migrants' Responsiveness to Weather Shocks*

	Dependent variable: Migrant Share of the Population			
	(1)	(2)	(3)	(4)
Precipitation z-scores lagged	-0.066***	-0.058***		
	[0.014]	[0.013]		
Precipitation levels lagged			-0.158***	-0.136***
			[0.036]	[0.032]
Precipitation z-scores at destination lagged	0.049***	0.045***		
	[0.012]	[0.012]		
Precipitation levels at destination lagged			0.116***	0.103***
			[0.031]	[0.028]
F statistic of joint significance	**22.76**	**21.40**	**19.50**	**17.85**
Time fixed effects	yes	yes	yes	yes
Destination fixed effects	yes	no	yes	no
Individual fixed effects	no	yes	no	yes
Socio-Economic control variables	yes	no	yes	no
R-squared	0.31	0.34	0.31	0.34
Observations	148,565	148,565	148,565	148,565
Number of destinations	205		205	
Number of individuals		24,152		24,152

All regressions use individual-level data and standard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. Unless noted otherwise, precipitation variables refer to origin area precipitation and are summed over the entire catchment area of each destination according to equation (1). Precipitation-levels are reported in decimeter of precipitation per month. Socio-economic control variables include dummy variables for gender, education level and age group.

Table A2: *Labour Market Response in Formal and Informal Sector with Precipitation Levels*

Panel A. Dependent variable: Log income per hour

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-1.07**	-0.23	-2.03**
	[0.469]	[0.378]	[0.830]
Precipitation levels lagged at destination	0.08**	0.05	0.09**
	[0.031]	[0.031]	[0.042]
F statistic of first stage relationship	18.96	18.71	17.92
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.12	0.13	0.08
Observations	100,545	54,008	61,150
Number of destinations	190	190	190

Panel B. Dependent variable: Employment

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.21*	-0.25**	-0.06
	[0.110]	[0.117]	[0.115]
Precipitation levels lagged at destination	-0.01	0.00	-0.01
	[0.008]	[0.009]	[0.009]
F statistic of first stage relationship	19.35	19.34	19.34
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.19	0.11	0.12
Observations	148,188	148,161	148,161
Number of destinations	190	190	190

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation levels as instrument for migrant share. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table A3: *Labour Market Response in Formal and Informal Sector with Precipitation Levels and Individual Fixed Effects*

Panel A. Dependent variable: Log income per hour

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-1.12**	-0.15	-2.28**
	[0.555]	[0.373]	[0.990]
Precipitation levels lagged at destination	0.07**	0.02	0.07*
	[0.028]	[0.022]	[0.037]
F statistic of first stage relationship	17.64	16.14	17.65
Time fixed effects	yes	yes	yes
Individual fixed effects	yes	yes	yes
Socio-Economic control variables	no	no	no
R-squared	0.05	0.07	0.04
Observations	98,929	52,438	60,306
Number of individuals	14,415	8,938	8,577

Panel B. Dependent variable: Employment

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.20*	-0.27**	-0.05
	[0.109]	[0.110]	[0.100]
Precipitation levels lagged at destination	-0.02**	-0.01	-0.01
	[0.007]	[0.006]	[0.007]
F statistic of first stage relationship	17.73	17.71	17.71
Time fixed effects	yes	yes	yes
Individual fixed effects	yes	yes	yes
Socio-Economic control variables	no	no	no
R-squared	0.02	0.01	0.01
Observations	144,635	144,606	144,606
Number of individuals	20,555	20,553	20,553

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation levels as instrument for migrant share. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummies for gender, education level and age group.

Table A4: *Labour Market Effects using Additional Years of Lagged Precipitation*

Dependent variable:	**Migrant Share of the Population**		**Log income per hour**	**Employment**
	(1)	(2)	(3)	(4)
Migrant share predicted from the first stage			-1.12**	-0.15*
			[0.528]	[0.094]
Precipitation	-0.035***	-0.037***		
	[0.010]	[0.010]		
Precipitation lagged 1 year	-0.053***	-0.053***		
	[0.010]	[0.010]		
Precipitation lagged 2 years	-0.032***	-0.029***		
	[0.007]	[0.007]		
Precipitation lagged 3 years	-0.011**	-0.013**		
	[0.005]	[0.006]		
Precipitation lagged 4 years	-0.024***	-0.024***		
	[0.009]	[0.008]		
Precipitation lagged 5 years		-0.005		
		[0.008]		
Precipitation at destination	0.028***	0.031***	0.02**	0.01**
	[0.009]	[0.009]	[0.011]	[0.003]
Precipitation at destination lagged 1 year	0.038***	0.038***	0.03**	-0.01***
	[0.010]	[0.009]	[0.013]	[0.003]
Precipitation at destination lagged 2 years	0.029***	0.029***	0.02	-0.00
	[0.007]	[0.007]	[0.012]	[0.003]
Precipitation at destination lagged 3 years	0.013***	0.016***	0.03**	0.01*
	[0.004]	[0.005]	[0.011]	[0.003]
Precipitation at destination lagged 4 years	0.029***	0.028***	0.04***	0.00
	[0.008]	[0.008]	[0.012]	[0.003]
Precipitation at destination lagged 5 years		0.012**		
		[0.006]		
F statistic of joint significance	5.63	4.89	5.22	5.60
Time fixed effects	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes
Socio-econ control variables	yes	yes	yes	yes
R-squared	0.34	0.34	0.12	0.19
Observations	148,565	148,565	100,611	148,300
Number of destinations	205	205	204	205

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. Unless noted otherwise, precipitation variables refer to origin area precipitation z-scores and are summed over the entire catchment area of each destination according to equation (1). Columns (3) and (4) use IV-2SLS and the instruments for migrant share are precipitation z-scores lagged 1 to 4 years. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table A5: *Labour Market Response in Formal and Informal Sector (rainfall weights constructed during panel period from 1988 to 2000)*

Panel A. Dependent variable: Log income per hour

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-1.23**	-0.31	-2.24**
	[0.531]	[0.405]	[0.922]
Precipitation destination lagged	0.04**	0.02	0.04**
	[0.015]	[0.014]	[0.021]
F statistic of first stage relationship	20.49	19.33	19.84
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.12	0.13	0.08
Observations	100,545	54,008	61,150
Number of destinations	190	190	190

Panel B. Dependent variable: Employment

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.26**	-0.32***	-0.02
	[0.124]	[0.107]	[0.131]
Precipitation destination lagged	-0.01**	-0.00	-0.01
	[0.004]	[0.004]	[0.005]
F statistic of first stage relationship	20.92	20.92	20.92
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.19	0.10	0.12
Observations	148,188	148,161	148,161
Number of destinations	190	190	190

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Rainfall weights in equation (1) are constructed using migration patterns during the panel period from 1988 to 2000. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is slightly smaller than in Table 4 in order to ensure that all destinations have sufficient observations across sectors. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table A6: *Heterogeneous Labour Market Impacts by Sector*
(rainfall weights constructed during panel period from 1988 to 2000)

Panel A. Dependent variable: Log income per hour	**All**		**Formal sector**		**Informal sector**	
	Low Education	**High Education**	**Low Education**	**High Education**	**Low Education**	**High Education**
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share predicted from the first stage	-2.33**	-0.25	-1.02	-0.08	-2.96***	-1.18
	[0.906]	[0.432]	[0.821]	[0.365]	[1.097]	[1.123]
Precipitation destination lagged	0.03	0.02	0.01	0.01	0.03	0.06*
	[0.017]	[0.019]	[0.018]	[0.019]	[0.021]	[0.036]
F statistic of first stage relationship	16.77	22.38	11.38	22.48	17.07	20.03
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes	yes	yes
R-squared	0.05	0.15	0.06	0.18	0.03	0.09
Observations	67,368	31,902	31,292	22,191	46,081	14,186
Number of destinations	173	173	171	172	173	173

Panel B. Dependent variable: Employment	**All**		**Formal sector**		**Informal sector**	
	Low Education	**High Education**	**Low Education**	**High Education**	**Low Education**	**High Education**
	(1)	(2)	(3)	(4)	(5)	(6)
Migrant share predicted from the first stage	-0.36	-0.04	-0.28*	-0.17	-0.14	0.11
	[0.230]	[0.121]	[0.159]	[0.138]	[0.212]	[0.141]
Precipitation destination lagged	-0.01***	-0.00	-0.00	-0.00	-0.01	-0.01
	[0.004]	[0.006]	[0.005]	[0.006]	[0.005]	[0.008]
F statistic of first stage relationship	15.71	22.90	15.71	22.93	15.71	22.93
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes	yes	yes
R-squared	0.13	0.26	0.09	0.15	0.09	0.09
Observations	95,523	50,529	95,508	50,517	95,508	50,517
Number of destinations	173	173	173	173	173	173

All regressions use individual-level data and stardard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Rainfall weights in equation (1) are constructed using migration patterns during the panel period from 1988 to 2000. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. Low-skilled individuals are defined as those with no or only primary education and high-skilled individuals are those with at least some secondary education. The number of observations is smaller than in Table 5 in order to ensure that all destinations have sufficient low- and high-skilled individuals in each sector. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table A7: *Labour Market Response using Origin Area Weights from the Intercensal Population Survey*

Panel A. Dependent variable: Log income per hour

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.84*	0.14	-1.91**
	[0.446]	[0.356]	[0.827]
Precipitation destination lagged	0.03**	0.01	0.04**
	[0.013]	[0.014]	[0.019]
F statistic of first stage relationship	20.46	19.23	18.78
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.12	0.13	0.08
Observations	99,516	53,429	60,569
Number of destinations	182	182	182

Panel B. Dependent variable: Employment

	Overall	Formal sector	Informal sector
	(1)	(2)	(3)
Migrant share predicted from the first stage	-0.08	-0.21**	0.10
	[0.107]	[0.099]	[0.129]
Precipitation destination lagged	-0.01***	-0.00	-0.01*
	[0.003]	[0.004]	[0.005]
F statistic of first stage relationship	22.79	22.80	22.80
Time fixed effects	yes	yes	yes
Destination fixed effects	yes	yes	yes
Socio-Economic control variables	yes	yes	yes
R-squared	0.19	0.11	0.12
Observations	146,597	146,570	146,570
Number of destinations	182	182	182

All regressions use individual-level data and standard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. All specifications use IV-2SLS with lagged precipitation z-scores as instrument for migrant share. Rainfall weights in equation (1) are constructed using migration patterns from the 1985 Intercensal Population Survey (SUPAS). Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. The number of observations is lower for income because this is only measured if a person is employed. Socio-economic control variables include dummy variables for gender, education level and age group.

Table A8: *Labour Market Response to Immigration (Destination-Level Analysis)*

	Dependent variable:					
	Log income per hour	Employment	Log income per hour	Employment	Log income per hour	Employment
	Reduced form		Second stage		Conley clusters	
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation	0.071**	0.034***				
	[0.033]	[0.011]				
Migrant share predicted from the first stage			-1.25**	-0.61***	-1.25**	-0.61***
			[0.610]	[0.230]	[0.594]	[0.212]
Precipitation destination lagged	-0.021	-0.031***	0.02	-0.01*	0.02*	-0.01**
	[0.023]	[0.008]	[0.014]	[0.006]	[0.012]	[0.005]
F statistic of first stage relationship			17.28	17.81	17.28	17.81
Time fixed effects	yes	yes	yes	yes	yes	yes
Destination fixed effects	yes	yes	yes	yes	yes	yes
Socio-Economic control variables	yes	yes	yes	yes	yes	yes
Observations	2,265	2,278	2,260	2,274	2,260	2,274
Number of destinations	200	200	195	196	195	196

This table uses data that is collapsed to the destination-year level. Standard errors are clustered at the destination level, *** p<0.01, ** p<0.05, * p<0.1. (1) and (2) show reduced form analyses; (3) and (4) use IV-2SLS with lagged precipitation z-scores as instrument for migrant share; (5) and (6) repeat columns (3) and (4) but use Conley spatial clusters. Log income per hour is measured in Indonesian Rupiah and employment is the share of individuals employed. Socio-economic control variables include destination level averages for gender, education level and age group.