State-sponsored migration and inequality: Evidence from New Order Indonesia

Graham K. Brown *

University of Western Australia
graham.brown@uwa.edu.au

January 23, 2015

Abstract

State-sponsored internal migration has been a relatively common developmental strategy historically, but has received surprisingly little attention. In this article, we present a simple economic model of state-sponsored migration and its impact on inequality, and test it on data from Indonesia's New Order regime, which had high levels of both state-sponsored and spontaneous internal migration. We find, as predicted, that state-sponsored migration has a detrimental impact on inequality in the destination district, while spontaneous migration reduces it. Moreover, this effect is particularly strong with respect to disaggregated 'horizontal' inequalities between ethnic groups, a major driver of ethnic violence. Because state-sponsored migration has often been implemented precisely as a response to security concerns over ethnically distinct peripheries, the conclusion we draw is that such policies may be counterproductive, exacerbating precisely those grievances that tend to lead to conflict.

1 Introduction

Contemporary studies of migration and development tend to fall into two broad categories. The first is a primarily economic perspective that assumes that migration is both voluntary and driven primarily by economic cost-benefit considerations (see, e.g., Borjas, 2014), a view datable to at least John Hick's assertion that 'differences in net economic advantages, chiefly differences in wages, are the main cause of migration' (Hicks, 1932, : p.72). The second, that has tended to preoccupy political scientists, sociologists and anthropologists more than economists, is 'forced' migration. While much of this latter literature has sought to break down a perceived unhelpfully absolute dichotomy of 'economic migrants' versus 'refugees', this has largely been at the expense of economic analysis—the contemporary and compendious *Oxford Handbook of Refugee and Forced Migration Studies* devotes not a single of its fifty-two chapters to the economics of forced migration (Fiddian-Qasmiyah et al., 2014). Our concern here, however, is with a third category that falls out of both sets of analysis: state-sponsored migration. By state-sponsored migration we mean population movements—inwards, outwards, or both—that are explicitly facilitated by state policy based on *incentives* rather than *coercion*. Just as there is a grey area between 'economic migrants' and 'refugees', there is clearly some ambiguity at the boundaries between what constitutes coercion and what constitutes incentives. Moreover, the two may be combined. Hence, for instance, the historic displacement of tens of thousands of ethnic Tibetans from the Tibetan regions of western China, particularly during the 1950s (i.e. forced out-migration), has been matched by state-sponsored in-migration of Han Chinese to the area (Fischer, 2008).

*The research for this paper used data drawn from the IPUMS International database (Minnesota Population Center, 2014), with data originally provided by Statistics Indonesia

In the contemporary era, examples of state-sponsored international in-migration are relatively few: Australia's 'Ten Pound Poms' (Hammerton and Coleborne, 2001) in the immediate post-World War Two era and Brazil's *embrancamento* (whitening) policy in the early decades of the twentieth century (Telles, 2004) are two obvious examples. In China, where emigrant 'Overseas Chinese' were once treated as 'traitors' subject to the death penalty (Yen, 1981), various local governments are now offering economic incentives, such as tax breaks, for their return (Murphy, 2000). State-sponsored (rather than directly forced) international out-migration, while a professed policy option for far right parties across Europe, is even less common historically. The founding of Liberia as a home for freed slaves from the Americas might be the most obvious example of such a policy where out-migration was achieved through incentives rather than coercion. In the contemporary era, the Philippines offers tax breaks for registered overseas workers.

Whereas examples of state-sponsored international migration are not common, there are many examples of state-sponsored internal migration particularly, in the contemporary era, in developing countries. Indonesia's *transmigrasi* policy–which provides our empirical focus here–is a well-known example, but in Southeast Asia alone, similar policies have been pursued in the Philippines, Thailand, Sri Lanka, and Vietnam. Such policies are usually framed in developmental terms, but Brown (2008) argues that these policies have often been undergirded by a political logic of settling 'loyal' ethnic citizens from core areas to troublesome ethnically-distinct peripheral regions. Short of their intended goal of pacification, however, Brown argues that the ethnic 'horizontal' inequalities generated by these policies instead exacerbated the feeling of marginalization among the local population in the receiving areas (see also Weiner, 1988).

Using the empirical example of internal migration in Indonesia—both voluntary and state-sponsored—we examine the economic dimension of state-sponsored migration more closely. The next section discusses how state-sponsored migration fits within existing economic theories of migration. Section 3 introduces the Indonesian case and the data used. Sections 4 and 5 examine, respectively, the individual- and district-level impacts of state-sponsored migration. Section 6 concludes.

2 Theoretical perspectives on state-sponsored migration

Mainstream economic perspectives on migration—whether internal (domestic) or international—are based on an underlying assumption that it is, in the long term, inequality-reducing, as migrants typically flow from low-income regions or countries to high-income regions or countries. While empirical evidence suggests that this has not in fact been consistently the case (see, e.g., Barham and Boucher, 1998; Phan and Coxhead, 2010), theoretical revision suggests that this is mainly due to relatively short-term effects, including an initial selection bias in who migrates in favor of the more highly educated (Borjas, 2014); and, short-term distortions in aggregate demand caused by the influx of migrants (Kanbur and Rapoport, 2005). Migration in developing countries–particularly rural-urban migration–has likewise been modelled as likely to lead to *increased* inequality, at least in the 'sending' community and at least in the short term. This is primarily because of the economic and social obstacles to migration among poorer members of the sending community, meaning that it is the relatively wealthy within a community that are able to benefit from the opportunities of migration (see, e.g. Milanovic, 1987; Medola, 2012) and it is their families in the sending community who will benefit from this via remittances. From this perspective, state-sponsored migration initiatives that reduce or eliminate the economic cost of migration should lead not only to a more optimal allocation of labour regionally but also reduce inequality (or at least prevent increased inequality) in the sending community by allowing poorer individuals and families access to the benefits from migration.

Borjas (2001) presents a simple two-region model of the decision to migrate based on wage incomes:

$$NetGain = \sum_{k=t}^{T} \frac{w_{jk} - w_{ik}}{(1+r)^{k-t}} - M \tag{1}$$

where:

- w_{jk} and w_{ik} are, respectively, the wage at age k in the destination region i and the region of origin j;

- t is the age at migration and T is the retirement age;
- r is the discount rate; and,
- M is the cost of the move, including the 'pyschic costs' of being away from friends and loved ones.

We can note of equation (1) that it assumes that the entire cost of the move is a one-off cost, outside of the summation term. While this seems plausible enough for the physical cost of the move itself, it might not be an entirely appropriate assumption in relation to the 'psychic costs'. In straightforward economic terms, the lifetime cost of an annual flight home—for Christmas, Chinese New Year, or Eid al-Fitri—is clearly linked to the duration of migration. On top of this, the 'psychic cost' of distance is likely to be linked to expected duration of migration—a three month visiting fellowship away from friends and loved ones is psychically more tolerable than a five-year secondment. It does not seem unreasonable, however, to assert that these on-going 'psychic costs' are similarly subject to discounting over time, as longer durations of migration will entail greater opportunities to make new friends and meet new loved ones. We can thus usefully partition the cost of the move M into one-off relocation expenses M^R and on-going annual 'psychic costs' M^P and rewrite equation (1) as:

$$NetGain = \sum_{k=t}^{T} \frac{w_{jk} - w_{ik} - M^P}{(1+r)^{k-t}} - M^R \tag{2}$$

This equation describes a situation in which migration is solely determined by 'pull' factors—advantageous economic incentives in one region induce individuals and families to relocate from one region to the other. If the state has a political or developmental interest in relocating people, however, then it must bear the cost of doing so under conditions where it is not economically advantageous. Indeed, the implication of the preceding equation is that the state will only need to 'sponsor' migration where the economic incentives are insufficient to 'pull' them. Discounting forced relocation, this implies that push factors operate through generating positive economic incentives to migrate where they are naturally negative.

We assume that the state has to compensate migrants to at least the extent that they would lose out—economically and 'psychically'—in relocating from j to i. Mirroring equation (2), we can write the net cost to the state of 'pushing' an individual to migrate as:

$$NetCost = \sum_{k=t}^{T} \frac{w_{jk} - w_{ik} + M^P}{(1+r)^{k-t}} + M^R \tag{3}$$

The implication of this, of course, is that the destination region i will now be host to differential expected wage rates, which we can term w_{ik}^L for the local wage at age k in region i and w_{ik}^M for the equivalent migrant wage. Assuming that the one-off costs of relocation M^R are, in grand scheme of things, not that large and absorbed by the state within its normal operating budget (or, in any case, not paid directly to the migrant), the average annual premium wage for migrants $P_i = w_{ik}^M - w_{ik}^L$ can be written as:

$$P_i = \frac{1}{T-t} \sum_{k=t}^{T} \frac{w_{jk} - w_{ik}^L + M^P}{(1+r)^{k-t}} \tag{4}$$

All this assumes full employment, however, so that the expected income in each region is indeed the prevailing wage rate in that region. In the classic Harris-Todaro model (Harris and Todaro, 1970), urban-rural migration—interpreted, sectorally, as a shift from the agricultural to the modern sector—is driven by the existence of a non-equilibrium wage in the modern sector, kept above the labour market equilibrium rate by unions or government policy. The consequent unemployment in the urban sector means that the migration calculus is one of *expected* wages, conditional on the probability of employment. In the Harris-Todaro model, uncertainty over employment prospects is manifest only in the receiving sector (the urban or modern sector) but not in the sending sector (the rural or agricultural sector); the latter is assumed to offer full employment opportunities. Hence, migration occurs when $W_R \cdot P_R > W_S$, where P_R is the probability of employment in the receiving (modern) sector (typically expressed as $1 - U_R$); and, W_R and W_S are, respectively, the wage rates in the receiving (modern) and sending (agricultural) sectors.

A common criticism of the Harris-Todaro model, however, is that it assumes that rural 'peasants' are risk-neutral—they will exchange a certain income in the agricultural sector (because U_A is assumed to be zero) for a marginally higher *expected* income in the modern sector, even if that carries a substantial risk of zero income. The Harris-Todaro model can be augmented with the inclusion of a informal sector in the urban regions that provides a basic income for the formally unemployed, W_I, such that the migration decision is given by $W_R \cdot (P_R) + W_I \cdot (1 - P_R) > W_S$. While this makes the migration decision more plausible theoretically, however, if the informal wage rate is lower than the rural wage $W_I < W_S$, the model still requires an assumption of minimally risk-neutral potential migrants in order to explain migration. Empirical evidence suggests, however, that people in the rural sector, particularly poorer people, are typically risk averse (see, e.g. Bonin et al., 2009). Clearly, risk-aversion in the Harris-Todaro model will reduce the likelihood of migration; in the extreme case, a completely risk-averse person would be unwilling to forego a guaranteed income in their home region for a uncertain income in their (potential) destination, even if the expected income is considerably higher.

Within a HT-type framework, the economic incentives in state-sponsored migration could operate through one or both of two channels. The state could (A) provide a wage supplement for migrants in the destination region $W_R^* > W_R$; or, (B) provide an additional guarantee of securing employment such that $P_R^* > 1 - U_R$. Without the ability or willingness to discriminate in employment—that is through channel (A) alone—state intervention to induce migration would be equivalent to simply raising the wage rate in the modern sector even further above the equilibrium price, with standard well-understood effects within the HT-model: an increase in migration, accompanied by an increase in unemployment. Moreover, the more risk averse the potential migrants, the higher the wage supplement would need to be to induce migration. Clearly, (A) is not an attractive policy option.

The alternative, hence, is for the state to provide some form of income guarantee to induce migration. This might be in the form of preferential access to public sector jobs in urban areas, or preferential land allocation in rural areas (see Figure 1 in Section 3). In the original Harris-Todaro model, full employment is assumed in the sending (rural) sector. In such circumstances, the state would clearly need to employ a combination of channels (A) and (B) to induce migration: a guaranteed income in the destination region would be insufficient to induce migration unless the wage rate was higher than that in the sending region (where income is also guaranteed). If this already obtains, of course, then the state has no need to induce migration—the economic incentives are already there. We are concerned, however, with a more general model of regional rather than sectoral migration, and the assumption of full employment in the region of origin hence cannot be sustained. Where there is employment uncertainty in the sending region, a guarantee of employment in the destination region may be sufficient to induce migration. Indeed, for risk-neutral potential migrants, the state can offer a *lower* wage than in the sending region, so long as $W_R > P_S \cdot W_S$. For risk averse potential migrants, this effect is exacerbated: a considerably lower guaranteed wage in the destination region may be considered preferable to an uncertain wage in the sending region.

In effect, then, what we have described is an almost complete reversal of the Harris-Todaro model. In the Harris-Todaro model of spontaneous migration, higher wages in the modern sector, despite uncertain employment, induce rural-urban migration. In the model we have described, by providing an employment guarantee in the receiving sector, the state is able to induce migration even at a lower wage than that in the sending region. In the following section, we test this model on the Indonesia data by examining the relative employment and conditional income of state-sponsored transmigrants vis-a-vis spontaneous migrants and non-migrants.

3 Transmigrasi in Indonesia: Background and data

In this section we provide an empirical analysis of the effects of state-sponsored migration on individual earnings and local inequality using census sample data from Indonesia. Indonesia provides an excellent case study for the analysis because of the scale of internal migration in the country and its varied forms. At the time of the 1990 census, 8.5 per cent of Indonesian citizens were residing in provinces other than that of their birth; by 2010, this figure had risen to 11.5 per cent. In addition to high levels of spontaneous migration, however, Indonesia also has a long history of 'transmigrasi'—state-sponsored migration that encourage out-migration from the overpopulated islands of Java and Bali to the less densely populated 'Outer Islands'. While transmigration programs date back to the Dutch colonial era, it was Suharto's New Order regime (1966-1998), that the transmigration program reached its zenith, with hundreds of thousands of families relocated from Java and Bali to the Outer Islands; many more 'unofficial' transmigrants followed.

The ostensible justification for the transmigration program was both developmental, based on the undoubted overpopulation in Java and Bali, and ideological, based on a nebulously defined need nation-building program (Hoey, 2003). Tirtosudarmo (2001), however, suggests an alternative motive—to provide a bedrock of Javanese support for the territorially-organized army, particularly in troublesome regions. While supported by the World Bank in its initial stages, the transmigration program has been subject to increasing critical attention, both in terms of its environmental impacts in encouraging deforestation (Fearnside, 1997) and its social impacts, particularly in relation to competition over resource control at the local level (Elmhirst, 1999). Transmigration sites often took prime agricultural land and displaced local populations in constructing amenities and infrastructure to service the new developments (Leith, 1998). Quantitatively, there is clear summary evidence that transmigrants benefitted from access to a disproportionate share of the agricultural land in the Outer Islands. Figure 1 shows the distribution of land-holding sizes among the indigenous population of the Outer Islands compared with transmigrants (defined here as people residing in the Outer Islands who were born in Java or Bali). It is limited to those who described their main industry of occupation as 'Agriculture'. The proportion of transmigrants with more than two hectares of land is almost double that of the local-born population, whereas the reverse is the case for those with less than one hectare of land.

The extent of migration in Indonesia and the particular nature of the transmigration program

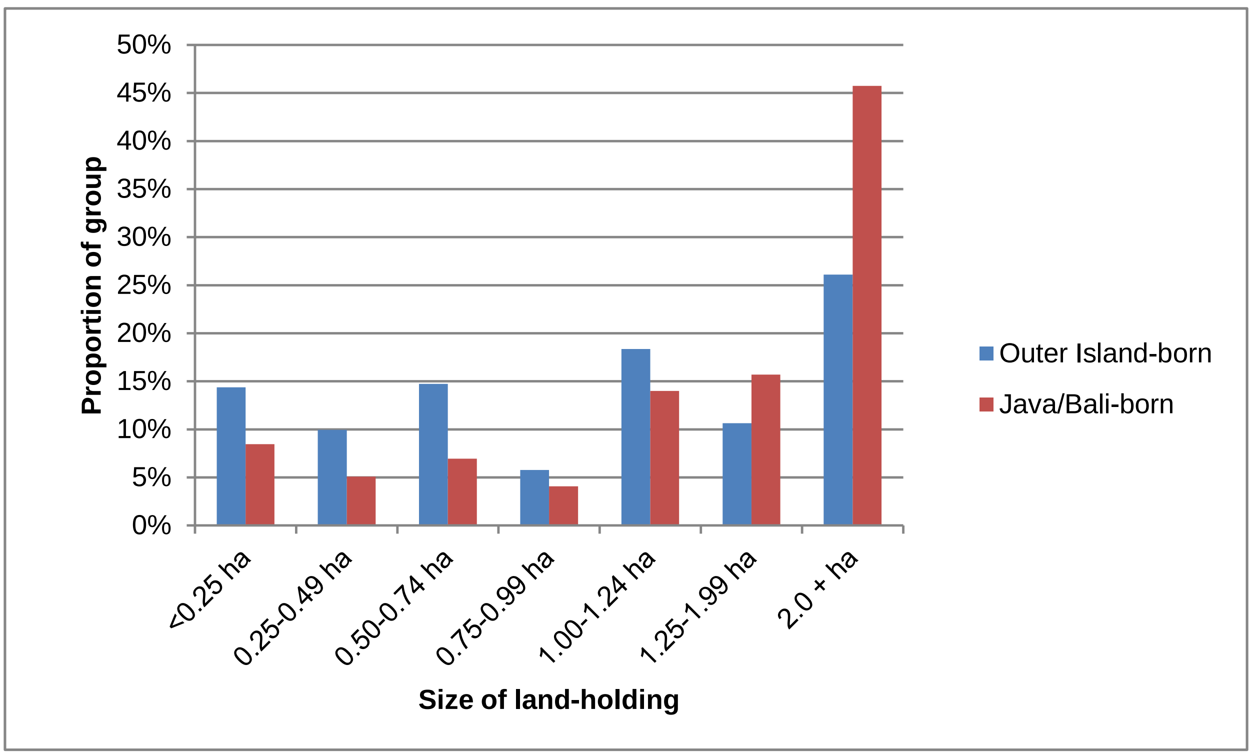

Figure 1: Land-holding of agriculturalists by province of birth, Outer Islands, 1990

3.1 Data

The main source of data we use for the empirical analysis is the 1995 Intercensal Survey (SUPAS, *Survei Penduduk Antar Sensus*). We use historical rather than contemporary data as the *transmigrasi* program, while still technically in operation, was radically scaled back following the 1997 financial crisis. The 1995 SUPAS was a 1% random sample of the previous 1990 census sample frame with additional questions relating to occupation and income.

While the 1995 SUPAS also contains a range of useful questions relating to migration history and status, it does not directly code for *transmigrasi* program; we hence need to create rules to define our populations of interest. Migration-related variables that we do have access to are: place of birth—both the first tier *propinsi* (provinces), and the second tier districts, which are divded into rural *kabupaten* and urban *kota*; place of previous residence; and, duration of residence in current locality. From this, we construct our categories as follows. Firstly, we define a 'migrant' as somebody who currently resides in a different province from that of their birth and who moved to their current locality at the age of 18 or over. The latter stipulation excludes from consideration the children of migrants who were born before their parents moved; this is because we are interested in the decision to migrate, and these children are likely to have had little active influence over the decision. It also exclude 'local' migration between districts within the same province; use of the term 'migrant' in the empirical sections should hence be understood as referring to *inter-provincial* migrants only, whether spontaneous or state-sponsored. This isolates the analysis from local rural-urban migration to provincial capitals.

Having defined our overall migrant group, we define 'transmigrants'—state-sponsored migrants—as those migrants who were born in Java or Bali but migrated to the Outer Islands. Other migrants—intra-Java/Bali migrants; migrants between the Outer Islands; and migrants from the Outer Islands to Java or Bali—we term 'spontaneous migrants'. This definition unavoidably conflates the official participants in the Transmigrasi programme with the unofficial transmigrants from Java and Bali to the Outer Islands, but insofar as we can assume that the determinants of non-official transmigration parallel those of 'spontaneous' migrants from other regions, the implication of this is that our results may if anything underestimate distinctive impacts of state-sponsored migration. Moreover, as we know historically that the transmigration program was primarily a rural-to-rural phenomenon, we disaggregate the results by urban/rural classification as far as possible; this gives us a closer picture of the actual impacts of transmigration. Even here, however, we should note that our definition of 'urban' corresponds to living within an urban metropolitan district (*kota*) and hence excludes those living in smaller urban areas of rural districts (*kabupaten*). While SUPAS does code for urban areas in *kabupaten*, the definition used by the Central Statistical Agency is primarily dependent on access to amenities, meaning that many areas that would normally be classified as 'rural' are classified as 'urban'.

In addition, we restrict our sample to those of normal working age—between 18 and 55 (the public sector retirement age in Indonesia)—and to males only. The latter restriction enables us to avoid problematic questions about differential participation in the labour market across the sexes, which would be particularly problematic in the Indonesian context, with wide cultural (and hence regional) variation in attitudes towards women's employment. Table 1 shows the distribution of the population according to our definitions of migrant status. The proportion of the different groups within our sample closely match those of the complete survey sample. For the individual-level analysis, we also provide alternative specifications that exclude the province of Jakarta when considering Java as a 'sending' region because of its special status as the national capital.

Other variables are constructed as follows. We define individuals as 'employed' if they reported working at least five out of the previous seven days in any type of employment, including self-employment. The 1995 SUPAS asked questions about income from a range of sources; we use the natural log of the total of income from all sources. For level of education, we construct a continuous variable for years of education completed. We also constructed and tested multiple categorical variables for completion of different stages of education, but the results on these variable did not vary significantly from the single continuous variable and are hence not reported.

Table 1: Distribution of population by migration status, %

	Complete survey (M+F)	Complete survey (M only)	Analysis sub-sample
Non-Migrants	83.7	82.4	81.6
Spontaneous Migrants	12.6	13.5	14.1
Transmigrants	3.6	4.1	4.3

4 Individual-level analysis

In this section, we examine the determinants of migration and its impacts on employment and earnings, and test whether there are significant differences between state-sponsored transmigrants and spontaneous migrants.

4.1 The decision to migrate

We model the decision to migrate through a simple probit estimation. The individual characteristic regressors we include are: age; age squared (to hold for return migration and non-linearity in the decision to migrate over time) and years of education. We also include two variables to capture the characteristics of the district of birth: a dummy variable for urban *kota* districts; and median income in district of birth to capture the relative wealth of the district of birth. The latter variable captures some of the economic 'push' factors in migration: all other things being equal, there is a relative disincentive economically to migrate away from a more wealthy district. We should note, however, that as this variable is calculated on the basis of 1995 incomes rather than district incomes at the time of migration, it is only really an approximation for local economic conditions at the time of migration and requires an assumption of stability in relative economic conditions at the district level over time. Standard errors are clustered on the district of birth.
Table 2 presents the results of this estimations. Model (1) includes all observations and behaves broadly as expected. Age is a non-linear predictor of migration status, initially increasing and then decreasing likelihood of migration; the maximum point comes at around 50 years of age. Education is a strong positive predictor of migration. As expected, higher incomes in the district of birth is a significant disincentive for migration, but there is no significant impact of being born in an urban district (over and above the typically higher median incomes in urban areas). The dummy variable for being born in Java or Bali is positive and significant; this translates into around five percentage points higher chance of migration for a Java/Bali-born individual than an similar Outer Islands-born individual.
g g Models (2) to (5) run the same model on geographically-partitioned samples: first by region of birth—whether in Java/Bali or in the Outer Islands; and, second by the urban/rural status of birth district. The individual-level characteristics in these partitioned results all produce remarkably consistent estimates as the overall model (1) both in terms of coefficient and statistical significance; indeed χ^2 tests (not reported) return no significant difference between the coefficients on age and education variables between any of models. Within these partitioned results, however, the district-level characteristics do vary considerably. Notably, while in the Outer Islands, both median income in district of birth and the urban status of the district of birth are significant predictors of out-migration, neither are significant for the Java/Bali subsample. Likewise, out-migration is significantly and negatively correlated with the relative wealth of the district in urban areas, but not in rural areas. In the rural subsample, the additional likelihood of out-migration from Java/Bali is notably higher than in the over model; the coefficient on Java/Bali in Model (4) corresponds to a increase of 8.8 percentage points in the likelihood of migration.

For the Java/Bali-born population, we can take the analysis another step and examine whether and how the determinants of spontaneous migration differ from those of state-sponsored transmigration. One

Table 2: Determinants of the decision to migrate by region of birth

	(1) All districts	(2) Outer Islands	(3) Java and Bali	(4) Rural districts	(5) Urban districts
Age	0.117***	0.109***	0.124***	0.106***	0.148***
	(0.00377)	(0.00638)	(0.00443)	(0.00327)	(0.00844)
Age, squared	-0.00123***	-0.00115***	-0.00130***	-0.00112***	-0.00153***
	(4.63e-05)	(7.75e-05)	(5.46e-05)	(4.28e-05)	(0.000107)
Years of Education	0.0813***	0.0898***	0.0777***	0.0863***	0.0726***
	(0.00310)	(0.00579)	(0.00349)	(0.00367)	(0.00525)
Median income (ln)	-0.521***	-0.316*	-0.392	-0.184	-1.083***
in district of birth	(0.148)	(0.131)	(0.201)	(0.127)	(0.299)
Born in urban district	0.138	0.468***	-0.175		
	(0.0986)	(0.0984)	(0.149)		
Born in Java/Bali	0.255***			0.484***	-0.230
	(0.0705)			(0.0616)	(0.129)
Constant	1.799	-0.647	0.476	-2.146	8.481*
	(1.780)	(1.588)	(2.375)	(1.540)	(3.642)
Observations	229,413	113,344	116,069	181,189	48,224
Pseudo R2	0.0887	0.107	0.0735	0.0957	0.118

Standard errors clustered on district of birth in parentheses
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

empirical strategy to do so would be to run a two-stage model that modelled a selection equation for the decision to migrate and a subsequent conditional equation for the type of migration (i.e. spontaneous—within Java/Bali—or transmigration to the Outer Islands). We prefer, however, to treat the decision as a single multinomial decision estimated through a multinomial probit. Psychologically, there seems no particular reason to prefer the sequential decision implied by the two-stage model ("Shall I migrate? OK; shall I take part in the transmigration programme?") over a simulataneous decision ("Shall I join the transmigration programme, or shall I move on my own initiative, or shall I stay put?"). Indeed, because the theoretical presumption is that state-sponsored migration may facilitate migration by individuals who wouldn't (or, economically, couldn't) migrate otherwise, the sequential decision seems, if anything, counterproductive—the first stage selection equation would 'hide' the characteristics of those who chose to migrate only because of the transmigration programme. There are hence strong theoretical reasons to treat the decision as multinomial rather than sequential. Pragmatically, this has the additional advantage that it allows us to more easily compare coefficients from the multinomial probit with the binary probits reported in Table 2.

Table 3 reports the results of this analysis. We run a multinomial probit on three outcome categories: non-migration (the base category); spontaneous migration; and, transmigration. The regressors are the same as those used in the binary probit above, but the population is restricted to those born in Java or Bali. As above, we run the model on the entire subpopulation—model (6)—and separately on those born in rural and urban districts. In all three models, the coefficient on education for transmigration is markedly lower than for spontaneous migration—around half the size—although still highly significant. The most marked difference is in the income level of the district of birth, however—in the partitioned results, the relative poverty of region of origin is a strong negative predictor of out-migration only for those born in urban districts. Figure 2 graphs the probability of different types of migration from Model (6) by the relative wealth of the district of birth for two levels of education: six years of education; and, twelve years. The stark difference between the effect of education and relative district wealth on the probability of spontaneous migration vis-à-vis transmigration is evident.

Table 3: Determinant of migration type, Java/Bali-born population only

	(6)		(7)		(8)	
	All districts		Rural districts		Urban districts	
Outcome category	Spontaneous	Transmigrant	Spontaneous	Transmigrant	Spontaneous	Transmigrant
Age	0.155***	0.176***	0.138***	0.171***	0.201***	0.189***
	(0.00811)	(0.00565)	(0.00819)	(0.00593)	(0.0150)	(0.0145)
Age, squared	-0.00163***	-0.00185***	-0.00148***	-0.00180***	-0.00206***	-0.00202***
	(9.99e-05)	(6.98e-05)	(0.000109)	(7.34e-05)	(0.000184)	(0.000180)
Years of Education	0.140***	0.0590***	0.155***	0.0623***	0.0994***	0.0544***
	(0.00661)	(0.00417)	(0.00667)	(0.00465)	(0.0122)	(0.0113)
Median income (ln)	-0.283	-0.770**	0.433	-0.458	-1.931***	-1.814***
in district of birth	(0.309)	(0.260)	(0.273)	(0.282)	(0.443)	(0.441)
Born in urban district	-0.254	-0.235				
	(0.233)	(0.176)				
Constant	-2.809	3.143	-11.01***	-0.475	16.47**	15.46**
	(3.659)	(3.070)	(3.299)	(3.330)	(5.420)	(5.411)
Observations	116,069		87,068		29,001	
Log likelihood	-60664		-47661		-12249	

Standard errors clustered on district of birth in parentheses
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

The empirical results presented in this section, then, largely confirm our expectations. Overall, these findings suggest that the marginal impact of individual attributes on migration likelihood are remarkably similar across Indonesia, but that both the overall likelihood and the geographic spread of out-migration differs in Java/Bali from the rest of the country, with a generally higher level of out-migration and less impact of the characteristics of region of birth. Comparing the results of model (2) with model (4) is most illustrative here: out-migration in the Outer Islands is strongly sourced from urban districts and from relatively poor districts; in contrast, out-migration in Java and Bali (excluding Jakarta), shows only very marginal impact of district characteristics on the decision to migrate. Across Indonesia, the decision to migrate is largely associated with relatively well-educated people from relatively poor regions—precisely the kind of person, intuitively, who has most to gain economically from seeking employment elsewhere. For Java/Bali-born individuals, however, the transmigration programme appears to have opened up migration possibilities to those with fewer educational resources.

4.2 Employment and income

In our discussion of the Harris-Todaro model, we concluded that in the presence of state-sponsored migration, we would expect to see higher employment rates for state-sponsored migrants but that, conditional on this advantageous selection into employment, we would not expect to see higher wages for state-sponsored migrants and, if potential migrants are risk averse, a (guaranteed) wage in the destination region lower than the uncertain wage in the sending region would suffice to induce migration. In order to test these expectations empirically on the Indonesian data, we need to take account of both an observational 'treatment effect'—selection into both types of migration may be influenced by unobserved characteristics that also influence employment chances and income (for instance, some latent measure of 'initiative')—and the censoring of income observations on selection into employment, which again may be—indeed, we expect to be—correlated with the characteristics of migrants of both types. We can estimate this as a fully recursive mixed process model (see Roodman, 2011), but the estimation is complicated by the different migration options available

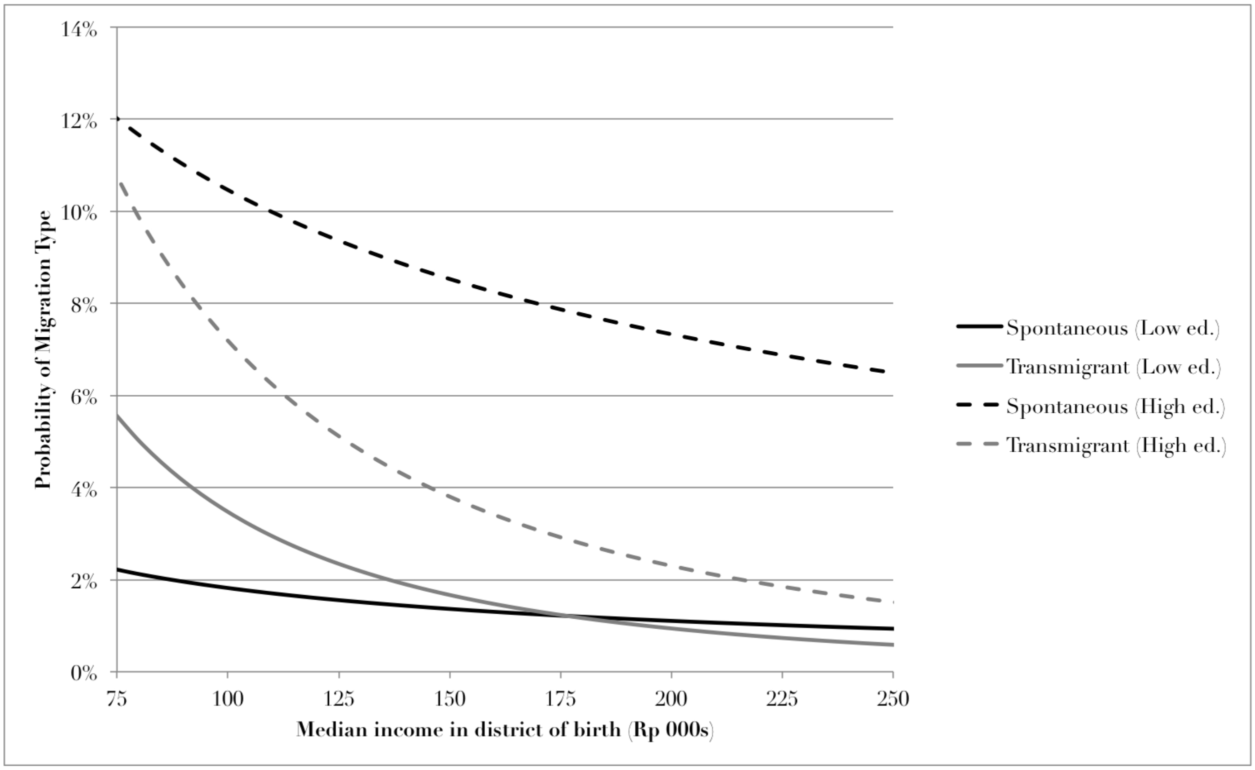

Figure 2: Estimated probability of migration by type, Java/Bali-born only
Source: Calculated from Model (6); all other variables held at mean

to the different populations. As modelled above, selection into migration for potential transmigrants (that is, the Java/Bali-born population) is a multinomial decision, while selection into migration for the Outer Islands-born population is a binomial decision. For a straightforward migration decision (stay or migrate), we could estimate the first stage of the recursive model as a standard binary treatment-effects model; or, we could model selection into different types of migration (stay, transmigrate, or migrate on own resources) using a multinomial treatment-effects model (see Deb and Trivedi, 2006). Both are problematic in this context. The former would not cater for the different determinants of state-sponsored and spontaneous migration for the Java/Bali-born population (see previous section), while the latter would incorrectly model transmigration as open to Outer Island-born populations. We hence need to 'manually' compute the first stage of the estimation by estimating the determinants of migration within the two sub-populations (Java/Bali-born and Outer Islands born) separately and then merging the estimated hazard functions of the propensity to migrate. Standard two-stage treatment-effects models proceed as follows: selection into the treatment (whether binary or multinomial) is modelled with a probit estimation; then, a hazard function calculated as the inverse Mills ratio of predicted likelihood of selection is used in place of the treatment variable in the outcome regression. For our purposes, we can manually compute two hazard functions for selection into transmigration and spontaneous migration as follows:

A Estimate predicted likelihood of selection into transmigration and spontaneous migration for the Java/Bali-born population with multinominal probit. This is equivalent to model (5) above;

B Estimate predicted likelihood of selection into spontaneous migration for the Outer Island-born population with binary probit. This is equivalent to model (2) above;

C Create a combined variable for selection into spontaneous migration that takes the appropriate predicted likelihood from [A] for the Java/Bali-born population and from [B] for the Outer Island-born population;

D Create a combined variable for selection into transmigration that takes the predicted likelihood from [A] for the Java/Bali-born population and the value 0 for the Outer Island-born population; and,

E Calculate the inverse Mills ratio of the two new variables in [C] and [D] and use these for the subsequent steps.

Having calculated this 'merged' first step, we can now use these results in a standard Heckman regression to estimate the impact of the different forms of migration on chances of employment and income conditional on employment. In addition to the hazard variables for selection into transmigration and selection migration, we include a standard Mincerian set of regressors: age (which can be interpreted as a proxy for experience) and years of education. For the employment selection equation, we include a squared transformation of both to hold for observable non-linearity in the relationship with employment likelihood. Table 4 reports the results of this estimation. The results largely confirm our expectations. Spontaneous migration confers no significant additional likelihood of selection into employment, but the transmigration variable is a strong and consistent positive predictor of selection into employment. This result holds across all the districts in the Outer Islands (model 9), and in separate regressions on the rural districts (model 10) and the urban districts (model 11). The control variables perform as expected. The picture that emerges from the final equation—income conditional on employment—is more complex. Although they receive no higher chance of employment than non-migrants, spontaneous migrants *do* enjoy a significant income advantage conditional on employment, both in the overall model and the partitioned urban and rural results. Transmigrants likewise enjoy a significant income advantage in urban areas. Indeed, in the urban areas estimation (model 11), the coefficient on the income advantage of the different forms of migration is not significantly different ($\chi^2 = 2.37$, $P > \chi^2 = 0.123$). In the rural areas, however, transmigrants did not experience a significant conditional income advantage. At this point it is worth remembering that our technical operationalization of transmigration was based on migration from Java to the Outer Islands at age 18 or above, irrespective of whether the move was to urban or rural areas. While this was the best definition for practical reasons (because we cannot track second and subsequent migrations), we know qualitatively that the destination regions for *actual* transmigrants was primarily rural. Hence, model 10 may give the best picture of the effect of transmigration, and this model most strongly confirms our theoretical expectations: transmigrants enjoy privileged selection into employment but no income advantage once employed, while spontaneous migrants experience the reverse.

For robustness, table 5 repeats the analysis in Table 4 but substitutes the two original binary variables for migrant type in place of the inverse Mills hazard function calculated for Table 4. This avoids the complexity of the previous estimation but requires the assumption that there are no important latent characteristics that influence both selection into migration and selection into employment. The directionality of results remain unaffected, but the coefficients on the impact of migration are considerably amplified. Overall, then, while these findings confirm that the transmigration programme facilitated migration of relatively less well-educated Javanese and Balinese (compared to their 'spontaneous' counterpart migrants across the archipelago) through privileged access to employment opportunities rather than direct income effects *per se*. The clear contrast in the nature of economic return for transmigrants–primarily through increased certainty of employment–versus spontaneous migrants–primarily through increased incomes conditional on employment–suggests that these two forms of migration may indeed have differential impact on inequality at the local level. It is to this that we turn in the next section.

5 Migration and inequality: District-level analysis

We can now turn to examine the impact of migration on inequality in the destination region. We calculate the Generalized Entropy (GE) index of inequality for each of the 188 districts in the Outer Islands; we use

Table 4: Effect of migration type on employment and income, Outer Islands

	(9) All Districts	(10) Rural Districts	(11) Urban Districts
OUTCOME: Income (ln)			
Age	0.0209***	0.0221***	0.0184***
	(0.000761)	(0.000948)	(0.00115)
Years of Education	0.0701***	0.0643***	0.0696***
	(0.00261)	(0.00267)	(0.00489)
Spontaneous Migrant	0.108***	0.0953***	0.111***
	(0.0155)	(0.0208)	(0.0226)
Transmigrant	0.0316*	-0.00621	0.0774***
	(0.0149)	(0.0174)	(0.0231)
Constant	10.86***	10.86***	10.98***
	(0.0427)	(0.0535)	(0.0929)
SELECTION: Employment			
Age	0.262***	0.181***	0.393***
	(0.0183)	(0.0145)	(0.0197)
Age, squared	-0.00352***	-0.00253***	-0.00513***
	(0.000216)	(0.000179)	(0.000230)
Years of Education	0.126***	0.0647**	0.124***
	(0.0172)	(0.0215)	(0.0257)
Years of Education, squared	-0.00434***	0.000420	-0.00634***
	(0.00110)	(0.00129)	(0.00137)
Spontaneous Migrant	-0.00958	0.0386	-0.0454
	(0.0278)	(0.0305)	(0.0328)
Transmigrant	0.127***	0.138***	0.119***
	(0.0216)	(0.0258)	(0.0290)
Constant	-4.256***	-2.595***	-6.384***
	(0.383)	(0.285)	(0.480)
athrho	-0.793***	-0.968***	-0.507***
	(0.0585)	(0.0615)	(0.0617)
ln sigma	-0.523***	-0.474***	-0.626***
	(0.0215)	(0.0219)	(0.0417)
Observations	26,316	16,868	9,448
Log likelihood	-28202	-18489	-9318

Bootstrapped standard errors clustered on district of current residence
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 5: Unadjusted effect of migration type on employment and income, Outer Islands

	(12) All Districts	(13) Rural Districts	(14) Urban Districts
OUTCOME: Income (ln)			
Age	0.0201***	0.0216***	0.0173***
	(0.000812)	(0.000992)	(0.00121)
Years of Education	0.0661***	0.0613***	0.0649***
	(0.00229)	(0.00250)	(0.00362)
Spontaneous Migrant	0.211***	0.183***	0.213***
	(0.0306)	(0.0374)	(0.0418)
Transmigrant	0.0775*	-0.00744	0.184***
	(0.0360)	(0.0356)	(0.0523)
Constant	10.90***	10.88***	11.03***
	(0.0443)	(0.0520)	(0.0857)
SELECTION: Employment			
Age	0.259***	0.176***	0.392***
	(0.0174)	(0.0120)	(0.0219)
Age, squared	-0.00348***	-0.00248***	-0.00512***
	(0.000209)	(0.000146)	(0.000253)
Years of Education	0.129***	0.0668**	0.129***
	(0.0188)	(0.0204)	(0.0277)
Years of Education, squared	-0.00452***	0.000200	-0.00654***
	(0.00111)	(0.00122)	(0.00148)
Spontaneous Migrant	0.0313	0.111	-0.0433
	(0.0476)	(0.0635)	(0.0677)
Transmigrant	0.279***	0.294***	0.266***
	(0.0416)	(0.0537)	(0.0592)
Constant	-4.213***	-2.525***	-6.395***
	(0.372)	(0.254)	(0.524)
athrho	-0.791***	-0.970***	-0.483***
	(0.0649)	(0.0599)	(0.0764)
ln sigma	-0.525***	-0.474***	-0.630***
	(0.0202)	(0.0205)	(0.0350)
Observations	26,316	16,868	9,448
Log likelihood	-28180	-18482	-9310

Standard errors clustered on district of current residence
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

the GE rather than the more familiar Gini coefficient because it can be disaggregated into between group and within group inequality. The GE measure is an extension of the Theil index to include an extra parameter, α, which affects the sensitivity of the measure to different portions of the distribution curve; the higher α, the more sensitive it is to changes at the upper end of the distribution curve. Algebraically, where y_i is the income of the ith individual in a population with a mean income of $\bar{y}$, $GE(\alpha)$ is given by:

$$GE(\alpha) = \frac{1}{\alpha^2 - \alpha}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\bar{y}}\right)^2 - 1\right] \tag{5}$$

with the special cases of $GE(0)$ and $GE(1)$ given by

$$GE(0) = \frac{1}{n}\sum_{i=1}^{n} log\frac{\bar{y}}{y_i} \tag{6}$$

and

$$GE(1) = \frac{1}{n}\sum_{i=1}^{n} \frac{y_i}{\bar{y}} log\frac{y_i}{\bar{y}} \tag{7}$$

$GE(\alpha = 1)$ equates to the original Theil index. We calculate the GE for four different values of α, -1, 0, 1, and 2. We regress these on the proportion of transmigrants and migrants in the working population (according to our oeprational definition given above). We also hold for overall level of income in the district and a dummy for whether the district is an urban kota or rural kabupaten. If our theoretical expectations are correct, we expect transmigration to be correlated with higher levels of inequality, but 'normal' migration to be correlated with lower levels of inequality.
Table 6 presents the results of this analysis. Of the control variables, average income is unsurprisingly strongly positively correlated with overall levels of income across all four values of α, while the dummy variable for urban kota is negative but insignificant, except where α=-1, when it is marginally significant at the 10% threshold. The coefficient on the impact of transmigration on inequality is progressively larger and more significant at higher values of α: with sensitivity set to the lower end of the distribution curve (α=-1), the coefficient is negative, although lacking significance ($P > |t| = 0.457$); with sensitivity set to the higher end of the distribution curve (α=2), however, the extent of transmigration is strongly and significantly positively correlated with overall levels of inequality. In contrast, as expected, the coefficient on 'normal' migration is consistently negative, although again of varying significance: with sensitivity set to lower ends of the distribution curve, it is only marginally significant (α=-1), or not at all (α=0); at sensitivity to the higher end of the distribution curve, it is moderately significant at the 5% threshold. Overall, then, this analysis confirms our theoretical predictions and the individual level evidence above that state-sponsored migration ('transmigration' in the Indonesian context) appears to increase inequality in the destination region, while 'normal' migration reduces it, but with the important caveat that this appears to be primarily through its relative impact at the higher end of the distribution curve (at least in our empirical case here).

We now turn to examine the impact of migration on the between-group element of inequality. As mentioned above, this may be of particular concern in developing countries as 'horizontal' inequalities between ethno-regional groups has been shown to be a strong explanatory factor for civil unrest and ethnic violence. Because Suharto's New Order regime did not collect data on ethnicity, we cannot directly access ethnic inequalities at the district level in this data. Instead, we use our three categories of migration as the groups for disaggregation: Java/Bali-born transmigrants; other migrants; and, local born non-migrants. It should be noted that while the first category of transmigrants is likely to be internally relatively homogenous—while there are major ethnic and religious differences between Java and Bali, the former is largely homogenous (except for Jakarta) and dwarfs the latter population-wise—while the other two categories are likely to hide some degree of internal ethnic heterogeneity depending, respectively, on the geographic spread of the region of origin and the internal diversity of the destination region (the local population in some districts, such as Gorontalo in North Sulawesi are almost completely ethnically homogenous, while others—particularly the

Table 6: Regression analysis: Migration and overall inequality, Indonesian outer islands, 1995

	Overall Inequality (GE)			
	$\alpha = -1$	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$
Average income	0.155***	0.0649**	0.113***	0.561***
	(0.0564)	(0.0318)	(0.0427)	(0.154)
Urban district	-0.0812**	-0.0252	-0.0101	-0.0216
	(0.0321)	(0.0181)	(0.0243)	(0.0874)
Java/Bali migrants (% of total pop.)	-0.0942	0.0302	0.189**	0.991***
	(0.126)	(0.0714)	(0.0956)	(0.344)
Other migrants (% of total pop.)	-0.299*	-0.152	-0.249**	-1.162**
	(0.166)	(0.0936)	(0.125)	(0.451)
Constant	-1.548**	-0.580	-1.189**	-6.645***
	(0.689)	(0.389)	(0.521)	(1.874)
Observations	188	188	188	188
R-squared	0.084	0.037	0.052	0.097

urban kota—are quite diverse). Using the standard disaggregation of the GE index at the four different values of α, we regress the same set of predictors against the between-group component of overall inequality; and the Kanbur/Zhang ratio of between-group to within-group inequality.[1] Table 7 and Table 8 report these results. The impact of migration on the level of between-group inequality is much more consistent and starker than its impact on overall inequality, whatever section of the distribution curve we focus on. The proportion of Java/Bali-born migrants in the population is positively correlated with the level of between-group inequality at a significance level below the 1% threshold for all values of α, while migration from other regions is negatively correlated with between-group inequality with either moderate significance (at the 5% threshold) for lower values of α or high significance for higher values of α. When we consider the ratio of between-group inequality to within-group inequality (Table 8), the contribution of 'normal' migration is again consistently negative but generally insignificant (except for marginal significance where α=1). The coefficient on transmigration is again consistently positive, but the size and significance of the coefficient varies in the opposite direction from Table 6; it is highly significant for lower values of α and not significant at all for α=2.

6 Conclusion

What can we conclude from this empirical enquiry? On the individual level, we found clear evidence in support of our theoretical hypothesis that state-sponsored migration operates primarily through providing additional certainty of income rather than higher expected incomes. When we turned to consider the impact of these different forms of migration on district-level inequality in the destination region, we found much stronger and more consistent evidence of a divergent impact. Higher levels of state-sponsored transmigration were associated with higher levels of inequality, a mechanism that appeared to work primarily through its contribution to between-group inequality and at the higher end of the distribution curve, although its impact in relative terms was more felt at the lower end. In contrast, higher levels of spontaneous migration was associated with lower levels of inequality, again particularly at higher ends of the distribution curve. It should of course be noted that our data is cross-sectional, and hence our ability to draw causal inferences is limited. But this interpretation corresponds well with our theoretical predictions, while the alternative interpretation—that for some reason, transmigration was directed towards areas with existing high levels of inequality, while spontaneous migrants were drawn to areas with existing low levels of inequality—would

[1] We also regressed separately against the within group component, but none of the results were significant and the overall model fits very low, so they have been omitted for space consideration.

Table 7: Migration and between-group inequality, Indonesian outer islands, 1995

	Between-Group Inequality (GE)			
	$\alpha = -1$	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$
Average income	0.0546***	0.0537***	0.0663***	0.105***
	(0.0111)	(0.0108)	(0.0136)	(0.0225)
Urban district	-0.00646	-0.00645	-0.00778	-0.0116
	(0.00635)	(0.00617)	(0.00773)	(0.0128)
Java/Bali migrants (% of total pop.)	0.0763***	0.0737***	0.0918***	0.151***
	(0.0250)	(0.0243)	(0.0305)	(0.0504)
Other migrants (% of total pop.)	-0.0829**	-0.0823**	-0.109***	-0.192***
	(0.0328)	(0.0319)	(0.0400)	(0.0661)
Constant	-0.663***	-0.650***	-0.803***	-1.280***
	(0.136)	(0.132)	(0.166)	(0.274)
Observations	188	188	188	188
R-squared	0.150	0.151	0.146	0.137

Table 8: Contribution of between-group inequality to overall inequality, Indonesian outer islands, 1995

	Kanbur/Zhang Ratio			
	$\alpha = -1$	$\alpha = 0$	$\alpha = 1$	$\alpha = 2$
Average income	0.0694***	0.119***	0.114***	0.0798***
	(0.0170)	(0.0256)	(0.0257)	(0.0222)
Urban district	-0.0111	-0.0199	-0.0226	-0.0220*
	(0.00965)	(0.0146)	(0.0146)	(0.0126)
Java/Bali migrants (% of total pop.)	0.120***	0.173***	0.138**	0.0464
	(0.0380)	(0.0573)	(0.0575)	(0.0497)
Other migrants (% of total pop.)	-0.0656	-0.132*	-0.122	-0.0674
	(0.0498)	(0.0752)	(0.0755)	(0.0651)
Constant	-0.830***	-1.429***	-1.359***	-0.933***
	(0.207)	(0.312)	(0.313)	(0.270)
Observations	188	188	188	188
R-squared	0.139	0.151	0.131	0.084

require a degree of theoretical conjuring to explain.
Historically, state-sponsored migration has been a relatively popular policy of developing countries, whether under the guise of opening up new lands for settlement, for reasons of political 'cohesion', or for more nebulous security-related concerns. To date, however, there has been little investigation of the economic impact of such policies as distinct from 'spontaneous' migration. In this article, we have presented a simple theoretical framework that suggests that state-sponsored migration, in contrast to standard expectations about spontaneous migration, is likely to be inequality-increasing rather than decreasing. We found empirical support for this assertion in comparing 'transmigrants' and spontaneous migrants under Indonesia's New Order regime. The implications of this study are important for political as well as economic reasons, however. If, as appears to be the case, 'horizontal' inequalities between ethnic groups is a major source of civil unrest and violence in developing countries, then state-sponsored migration programmes may exacerbate rather than mitigate these risks where ethnic groups are geographically segregated in their 'home' regions. While Indonesia is the clearest case where such a policy was undertaken precisely to address the potential political problem of ethnically distinct peripheries, similar policies can be seen in many other places including, inter alia: China, where substantial Han migration to the restive regions of Tibet and Xinjiang was sponsored by the state; Sri Lanka, where a policy of 'opening up' the dry land brought substantial numbers of Singhalese settlers into predominantly Tamil areas; and, the Philippines, where policies of resettling Christian groups into Muslim-dominated Mindanao were begun during the American colonial era and accelerated in the early independence era. Although further empirical investigation would be necessary in order to establish how far the Indonesian experience is generalizable, the findings of this article suggest that short of dealing with a security problem, these policies may have counterproductively exacerbated the grievances underlying ethnic rebellion.

References

B. Barham and S. Boucher. Migration, remittances, and inequality: Estimating the net effects of migration on income distribution. *Journal of Development Economics*, 55:307–331, 1998.

H. Bonin, A. Constant, K. Tatsiramos, and K. F. Zimmermann. Native-migrant differences in risk attitudes. *Applied Economics Letters*, 16:1581–1586, 2009.

G. J. Borjas. *Immigration Economics*. Harvard University Press, Cambridge, Mass., 2014.

G. K. Brown. Horizontal inequalities and separatism in Southeast Asia: A comparative perspective. In F. Stewart, editor, *Horizontal Inequalities and Conflict: Understanding Group Violence in Multiethnic Societies*. Palgrave, Basingstoke, 2008.

P. Deb and P. K. Trivedi. Specification and simulated likelihood estimation of a non-normal treatment-outcome model with selection: Application to healthcare utilization. *The Econometrics Journal*, 9:307–331, 2006.

R. Elmhirst. Space, identity politics and resource control in Indonesia's transmigration programme. *Political Geography*, 18:813–835, 1999.

P. M. Fearnside. Transmigration in Indonesia: Lessons from its environmental and social impact. *Environmental Management*, 21:553–570, 1997.

E. Fiddian-Qasmiyah, G. Loescher, K. Long, and N. Sigona, editors. *The Oxford Handbook of Refugee and Forced Migration Studes*. Oxford University Press, Oxford, 2014.

A. M. Fischer. "Population invasion" versus urban exclusion in the Tibetan areas of western China. *Population and Development Review*, 34:631–662, 2008.

J. Hammerton and C. Coleborne. Ten-pound poms revisited: Battlers' tales and Britist migration to Australia, 1947–1971. *Journal of Australian Studies*, 25:86–96, 2001.

J. R. Harris and M. P. Todaro. Migration, unemployment, and development: A two-sector analysis. *The American Economic Review*, 60:126–142, 1970.

J. R. Hicks. *The Theory of Wages*. MacMillan, London, 1932.

B. A. Hoey. Nationalism in Indonesia: Building imagined and intentional communities through transmigration. *Ethnology*, 42:109–126, 2003.

R. Kanbur and H. Rapoport. Migration selectivity and the evolution of spatial inequality. *Journal of Economic Geography*, 5:43–57, 2005.

J. Leith. Resettlement history, resources and resistance in North Halmahera. In S. Pannell and F. von Benda-Beckmann, editors, *Old World Places, New World Problems: Exploring Issues of Resource Management in Eastern Indonesia*. Australia National University, Centre for Resource and Environmental Studies, Canberra, 1998.

M. Medola. Rural out-migration and economic development at origin: A review of the evidence. *Journal of International Development*, 24:102–122, 2012.

B. Milanovic. Remittances and income distribution. *Journal of Economic Studies*, 14:24–37, 1987.

Minnesota Population Center. *Integrated Public Use Microdata Series, International: Version 6.3*. University of Minnesota, Minneapolis, 2014. Machine-readable database.

R. Murphy. Return migration, entrepreneurship and local state corporatism in rural China: The experience of two counties in south Jiangxi. *Journal of Contemporary China*, 9:231–247, 2000.

D. Phan and I. Coxhead. Inter-provincial migration and inequality during Vietnam's transition. *Journal of Development Economics*, 91:100–112, 2010.

D. Roodman. Fitting fully observed recursive mixed-process models with cmp. *Stata Journal*, 11:159–206, 2011.

E. E. Telles. *Race in Another America: The Significance of Skin Color in Brazil*. Princeton University Press, Princeton, 2004.

R. Tirtosudarmo. Demography and security: Transmigration policy in Indonesia. In M. Weiner and S. S. Russell, editors, *Demography and National Security*. Berghahn Books, Oxford, 2001.

M. Weiner. *Sons of the Soil: Migration and Ethnic Conflict in India*. Oxford University Press, Oxford, 1988.

C.-H. Yen. Ch'ng changing images of Overses Chinese (1644–1912). *Modern Asian Studies*, 15:261–285, 1981.